International Journal of Innovative Research and Review ISSN: 2347 – 4424 (Online)
An Online International Journal Available at http://www.cibtech.org/jirr.htm
2016 Vol. 4 (2) April-June, pp.40-53/Singh et al.
Research Article

COINTEGRATION AND CAUSALITY: AN APPLICATION TO GDP AND MAJOR SECTORS OF NIGERIA

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ABSTRACT
The research investigated integration *viz.* GDP, Agriculture; Industry and Services sectors of Nigeria using Johansen's multivariate co-integration approach. Findings confirmed the presence of co-integration, implying long-run association among the four-variables. For additional evidence as to whether and in which direction transmission occurred between the pairs, Granger causality test confirmed all the variables to be determining factor in revenue formation. However, all the variables were found efficient as depicted by bidirectional causal relationships among them. Also, the impulse response functions validate the results of co-integration and Granger causality, but the magnitude of revenue transmission of Services to GDP was found to exhibit more effect when compared to impulse shocks from Agriculture and Industry on GDP. The major implication is to design a network of economic development that will enhance economic growth; economic integration and better transmission among them.

Keywords: *Co-integration, Causality, VECM, IRFs, Forecast, GDP, Sectors, Nigeria*

INTRODUCTION
Economic development is a term that economists, politicians and others have used frequently since the 20th Century. The concept, however, has been in existence in the West for centuries. The term refers to economic growth accompanied by changes in output distribution and economic structure. It is concerned with quality improvements, the introduction of new goods and services, risk mitigation and the dynamics of innovation and entrepreneurship. Economic development has direct relationship with the environment. Whereas economic development is a policy intervention endeavour with aims of economic and social well-being of people, economic growth is a phenomenon of market productivity and rise in GDP. Consequently, as an economist Amartya Sen points out, "economic growth is one aspect of the process of economic development.

Initially, the agricultural sector, driven by the demand for food and cash crops production was at the centre of the growth process, contributing 54.7 per cent to the GDP during the 1960s. Nigeria's economic aspirations have remained that of altering the structure of production and consumption patterns, diversifying the economic base and reducing dependence on oil, with the aim of putting the economy on a part of sustainable, all-inclusive and non-inflationary growth. The implication of this is that while rapid growth in output, as measured by the real gross domestic product (GDP), is important, the transformation of the various sectors of the economy is even more critical. This is consistent with the growth aspirations of most developing countries, as the structure of the economy is expected to change as growth progresses.

Looking back, it is clear that the economy has not actually performed to its full potential, particularly in the face of its rising population; economy has grossly underperformed relative to her enormous resource endowment and her peer nations, i.e. the economic performance has been rather weak and does not reflect these endowments. Compared with the emerging Asian countries, notably, Thailand, Malaysia, China, India and Indonesia that were far behind Nigeria in terms of GDP per capita in 1970, these countries have transformed their economies and are not only miles ahead of Nigeria, but are also major players on the global economic arena. The prospects for the economy depend on the policies articulated for the medium-to-long term and the seriousness with which they are implemented. Keeping in mind these challenges, this study aimed at investigating the progress of Nigerian economic growth with the view of exploring possible prospects using VAR and ARIMA techniques.

MATERIALS AND METHODS

Research Methodology

Nigeria is located in West Africa on the Gulf of Guinea and has a total area of 923,768 km^2 (356,669 sq mi), making it the world's 32^{nd} largest country. The country was ranked 30th in the world in terms of GDP in 2012, and envisaged to record the highest average GDP growth in the world between 2010 and 2050. The country is one of two countries from Africa among 11 Global Growth Generators countries. This study used yearly data *viz.* GDP, Agricultural; Industrial and Services sectors respectively, of Nigeria, spanning from 1990-2012, sourced from database of Central Bank of Nigeria; National Bureau of Statistics; Bulletins etc. For the VAR analysis all the series were transformed into natural log-form to eliminate variations in movement due to level differences. Details of analytical techniques used are given below.

Model Selection Criteria

The information criteria are computed for the VAR models of the form:

$Y_t = A_1Y_{t-1} + \ldots.. + A_nY_{t-n} + B_q X_t + \ldots\ldots.. + B_qX_{t-q} + CD_t + \mathcal{E}_t$ ……………………. (1)

Where Y_t is *K*-dimensional. The lag order of the exogenous variables X_t, q, and deterministic term D_t have to be pre-specified. For a range of lag orders n the model is estimated by OLS. The optimal lag is chosen by minimizing one of the following information criteria:

AIC (n) = $\log \det \{ \sum_u(n))\} + (2/T)\, nK^2$ ……………………….. (2)

HQIC (n) = $\log \det \{\sum_u(n)\} + (2\log \log T/T)\, nK^2$ ………………….. (3)

SBIC (n) = $\log \det \{\sum_u(n)\} + (\log T/T)\, nK^2$ …………………………… (4)

FPE (n) = $(T + n^*/T-n^*)^k \det \{\sum_u(n)\}$ …………………………….. (5)

Where $\sum_u(n)$ is estimated by $T^{-1} \sum_{t=1}^{T} Ut U^1t$, n^* is the total number of parameters in each equation of the model when n is the lag order of the endogenous variables, also counting the deterministic terms and exogenous variables. The sample length is the same for all different lag lengths and is determined by the maximum lag order.

Augmented Dickey-Fuller (ADF) Unit Root Test

An implicit assumption in Johansen's co-integration approach is that the variables should be non-stationary at level, but stationary after first differencing. The Augmented Dickey-Fuller test was used to check the order of integration and it is given below:

$\Delta Y_t = \alpha + \delta T + \beta_1 Y_{t-1} + \sum_{i=1}^{p} \beta_i\, \Delta Y_{t-1} + \mathcal{E}_i$ ……………………………. (6)

where, $\Delta Y_t = Y_t - Y_{t-1}$, $\Delta Y_{t-1} = Y_{t-1} - Y_{t-2}$, and $\Delta Y_{t-2} = Y_{t-2} - Y_{t-3}$, etc $\mathcal{E}_i$ is pure white noise term; α is the constant-term, *T* is the time trend effect, and *p* is the optimal lag value which is selected on the basis of Hannan–Quinn information criterion (HQIC), Akaike information criteria (AIC), Schwarz Bayesian information criterion (SBIC). The null hypothesis is that β_1, the coefficient of Y_{t-1} is zero. The alternative hypothesis is: $\beta_1 < 0$. A non-rejection of the null hypothesis suggests that the time series under consideration is non-stationary (Gujarati, 2012; Beag and Singla, 2014).

Co-integration Analysis Using Johansen Method

The Johansen procedure examines a vector auto regressive (VAR) model of Y_t, an (n x 1) vector of variables that are integrated of the order I(1) time series. This VAR can be expressed as follow:

$\Delta Y_t = \mu + \sum_{t=1}^{p-1} \Gamma_i Y_{t-1} + \Pi\, Y_{t-1} + \mathcal{E}i$ …………………………….. (7)

Where, Γ and Π are matrices of parameters, *p* is the number of lags (selected on the basis of HQIC, AIC and SBIC), Ɛi is an (n x 1) vector of innovations. The presence of at least one co-integrating relationship is necessary for the analysis of long-run relationship of the series to be plausible. To detect the number of co-integrating vectors, Johansen proposed two likelihood ratio tests: Trace test and Maximum Eigen-value test, shown in Equations (8) and (9), respectively:

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Jtrace = $-T \sum_{i=r+1}^{n} \ln(1-\lambda i)$ …………………………………….. (8)

Jmax = $-T \ln(1-\lambda r + 1)$ ………………………………………… (9)

Where, T is the sample size and λi is the i^{th} largest canonical correlation. The Trace test examines the null hypothesis of r co-integrating vectors against the alternative hypothesis of n co-integrating vectors. The maximum Eigen-value test, on the other hand, tests the null hypothesis of r co-integrating vectors against the alternative hypothesis of $r+1$ co-integrating vectors (Hjalmarsson and Osterholm, 2010; Beag and Singla, 2014).

Granger Causality Test

The Granger causality test conducted within the framework of a VAR model was used to test the existence and the direction of long-run causal relationship between the series (Granger, 1969; Beag and Singla, 2014). It is an F-test of whether changes in one series affect another series. Taking the causality relationship between GDP and Agriculture sector as an example, the test was based on the following pairs of OLS regression equations through a bivariate VAR:

$Pln\ GDP_t = \sum_{i=1}^{m} \alpha_I\ PlnGDP_{t-1} + \sum_{i=1}^{m} \beta_j\ PlnA_{t-1} + \mathcal{E}i$ …………………… (10)

$Pln\ A_t = \sum_{i=1}^{m} Y_i\ PlnA_{t-1} + \sum_{i=1}^{m} \delta_j\ PlnGDP_{t-1} + \mathcal{E}i$ ………………………… (11)

Where, GDP and A are GDP and Agriculture, *Pln* stands for income series in logarithm form and t is the time trend variable. The subscript stands for the number of lags of both variables in the system. The null hypothesis in Equation (10), i.e. H_0:$\beta_1 = \beta_2 = \ldots\ldots\ldots = \beta_j = 0$ against the alternative, i.e., H_1: Not H_0, is that $PlnA_t$ does not Granger cause *PlnGDP*. Similarly, testing H_0: $\delta_1 = \delta_2 = \ldots\ldots = \delta_j = 0$ against H_1: Not H_0 in Equation (11) is a test that $P\ ln\ GDP_t$ does not Granger cause *PlnAt*. In each case, a rejection of the null hypothesis will imply that there is Granger causality between the variables (Gujarati, 2010).

Impulse Response Functions

Granger causality tests do not determine the relative strength of causality effects beyond the selected time span. In such circumstances, causality tests are inappropriate because these tests are unable to indicate how much feedback exists from one variable to the other beyond the selected sample period (Rahman and Shahbaz, 2013). The best way to interpret the implications of the models for patterns of revenue transmission, causality and adjustment are to consider the time paths of revenues after exogenous shocks, i.e. impulse responses. The impulse response function traces the effect of one standard deviation or one unit shock to one of the variables on current and future values of all the endogenous variables in a system over various time horizons (Rahman and Shahbaz, 2013). For this study the generalized impulse response function (GIRF) originally developed by Koop *et al.*, (1996) and suggested by Pesaran and Shin (1998) was used. The GIRF in the case of an arbitrary current shock, δ, and history, ω_{t-1} is specified below:

$GIRF_Y (h, \delta, \omega_{t-1}) = E\ [Y_t + h|\delta, \omega_{t-1}] - E\ [y_{t-1}|\omega_{t-1}]$ ………………………. (12)

For n = 0, 1

Vector Error Correction Model

If all series follow an integrated process of I(1), vector error correction model that accounts for trends and a constant term is specified as follow:

$\Delta P_i = \prod P_{t-1} + \sum_{i=1}^{L-1} \Gamma_I + \Delta P_{t-1} + \Delta P_{t1} + V + \delta_t + \mathcal{E}i$ ………………………………. (13)

Where ΔP_{t-1} a vector of $m\ x\ 1$ first difference is prices from m markets and $\prod$ is a coefficient matrix and point of interest to test for co-integration and adjustments between markets. If $\prod$ has a reduced rank of $r < m$, then there exist $n\ x\ r$ matrices of α and β each with rank r, such that $\prod = \alpha\beta$, where α is a vector of the co-integration equation parameters $\Gamma 1, \ldots\ldots\ \Gamma_n, \Gamma_{L-1}$ are parameters of the lagged short – term reactions to the previous price changes (ΔP_{t-k}) in all markets. δ is a parameters of trend and V is a constant term.

Here, one should note that since the VECM equation specified earlier is based on first differences, the constant implies a linear time trend in the differences, and the time trend (δt) implies a quadratic time trend in the levels of the data. $\mathcal{E}i$ is a vector of $m\ x\ 1$ disturbance term assumed to be identically and independently distributed. L refers to the number of lags determined from the vector autoregressive (VAR) analysis.

ARIMA Model

According to Box and Jenkins (1976) as cited by Dasyam *et al.*, (2015), a non seasonal ARIMA model is denoted by ARIMA (p,d,q) which is a combination of Auto Regressive (AR) and Moving Average (MA) with an order of integration or differencing (d), where p and q are the order of autocorrelation and moving average respectively (Gujarati *et al.*, 2012).

The Auto-regressive model of order p denoted by AR(p) is as follows:

$Z_t = c + \varnothing_1 Z_{t-1} + \varnothing_2 Z_{t-2} + \ldots + \varnothing_p Z_{t-p} + \varepsilon_t$ ………………………… (14)

Where c is constant term, $\varnothing_p$ is the p-th autoregressive parameter and ε_t is the error term at time *t*.

The general Moving Average (MA) model of order q or MA(q) can be written as:

$Z_t = c + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \ldots - \theta_q \varepsilon_{t-q}$ ……………………….. (15)

Where, c is constant term, θ_q is the q-th moving average parameter and ε_{t-k} is the error term at time t-k.

ARIMA in general form is as follows:

$\Delta^d Z_t = c + (\varnothing_1 \Delta^d Z_{t-1} + \ldots + \varnothing_p \Delta^d Z_{t-p}) - (\theta_1 \varepsilon_{t-1} + \ldots + \theta_q \varepsilon_{t-q}) + \varepsilon_t$ …………… (16)

Where, Δ denotes difference operator like

$\Delta Z_t = Z_t - Z_{t-1}$ …………………….. (17)

$\Delta^2 Z_{t-1} = \Delta Z_t - \Delta Z_{t-1}$ …………………….. (18)

Here, $Z_{t-1}, \ldots, Z_{t-p}$ are values of past series with lag 1, …, p respectively.

Forecasting Accuracy

For measuring the accuracy in fitted time series model, mean absolute prediction error (MAPE), relative mean square prediction error (RMSPE) and relative mean absolute prediction error (RMAPE) were computed using the following formulae (Ranjit, 2014):

MAPE = $1/T \sum \{At - Ft\}$ ………………………………. (19)

RMPSE = $1/T \sum \{(At - Ft)^2 / At\}$ ………………………….. (20)

RMAPE = $1/T \sum \{(At - Ft)^2 / At\} X\ 100$ …………………… (21)

Where, At = Actual value; Ft = Future value, and T= Time period(s)

RESULTS AND DISCUSSION

Lag Selection Criteria

In order to avoid biasness in test for stationarity due to sensitivity of time series to lag length; test for co-integration or fit co-integrating VECMs, it become imperative to specify how many lags to include in the model. Building on the research work of Maddala and Kim (1998); Nielsen (2001); Becketti (2013); Gujarati (2012); Maddala and Lahiri (2013) and Sundaramoorthy *et al.*, (2014), it was found that the methods implemented in vector autoregressive selection-order criteria can be used to determine the lag order for a vector autoregressive model with I(1) for variables. The output below uses vector autoregressive selection order criteria to determine the lag order of the VAR of the time series data. Results *viz.* VAR selection criteria advised us to use three lags for this four-variable model because the Hannan–Quinn information criterion (HQIC), Akaike information criteria (AIC), Schwarz Bayesian information criterion (SBIC) method, and sequential likelihood-ratio (LR) tests all selected three lag, as indicated by asterisk '*' shown in Table 1. In other words, it can be verified that when all the time series data were used, the LR test; AIC; HQIC and SBIC methods advised that we selects three lag for the four-variable model. It should be noted that when all the criteria agree, the selection is clear, but in situation of conflicting results, the selection criteria with the highest lag order is considered or chosen.

Table 1: Lag Selection Criteria

Lag	LR	AIC	HQIC	SBIC
0		-2.6	-2.64	-2.44
1	163.09	-9.2	-8.99	-8.19
2	52.30	-10.2	-9.86	-8.41
3	49.82*	-11.1*	-10.59*	-8.51*

Source: STATA Computer printout

Note: * indicate chosen lag number by a selection criterion

Unit Root Test

The Augmented Dickey Fuller (ADF) test (Dickey and Fuller, 1979; Dickey and Fuller, 1981; Dickey, 1990; as cited by Maddala and Lahiri, 2013) was used and the presence of unit root was checked under different scenarios of the equation such as with intercept, with intercept and trend, and none (Table 2). The results of the Augmented Dickey-Fuller (ADF) unit root test applied at level and first difference to the logarithmically transformed variables series are given in Table 1.

Results of the unit root test did not reject the null hypothesis of presence of unit root when the series were considered at level as the absolute values of the test statistics were below the 5 per cent test critical values.

Furthermore, a unit root test of first difference was conducted, which found the series to be stationary as absolute values of the test statistics were greater than the 5 per cent test critical values. With the evidence that the series were non-stationary and integrated of the order 1 i.e. I(1), test for co-integration among these variables using Johansen's maximum likelihood approach was applied.

Table 2: ADF Unit Root Test

Variables	Stage	T- Statistic	T-Critical Value (5%)	Remarks
GDP	At Level	3.334	3.000	Non-stationary
	First Difference	1.604	1.345**	Stationary
Agriculture	At Level	1.830	3.000	Non-stationary
	First Difference	3.019	3.000**	Stationary
Industry	At Level	2.00	3.000	Non-stationary
	First Difference	2.403	1.761**	Stationary
Services	At Level	0.364	3.600	Non-stationary
	First Difference	4.307	3.600**	Stationary

Source: STAT Computer printout

Note: Asterisks ** indicate that unit root at level or in the first differences were rejected at 5 per cent significance

Multivariate Johansen Co-integration Test

The test for co-integration implemented in vector error correction rank was based on Johansen's method. Results of Johansen's maximum likelihood tests (maximum-eigen value and trace tests) are presented in Table 3.

To check the first null hypothesis that the variables were not co-integrated ($r = 0$), trace and maximum statistics were calculated, both of which rejected the null hypotheses as trace and maximum test statistics values were higher than 5 per cent critical values and accepted the alternative of one or more co-integrating vectors.

Similarly, the null hypotheses: $r \leq 1$ and $r \leq 2$ from both statistics were rejected against their alternative hypotheses of $r \geq 1$and $r \geq 2$, respectively. The null hypothesis $r \leq 3$ from both the tests (trace and maximum tests) were accepted and their alternative hypotheses ($r = 4$) were rejected as the trace and maximum statistics were below their corresponding critical values at 5 per cent level of significance. Both these tests confirmed that all the four variables had 3 co-integrating vectors out of 4 co-integrating equations, indicating that they are well integrated and signals are transferred from one variable to the other to ensure efficiency.

In other words, using all four series and a model with three lags, results indicated that there exist three co-integrating relationships. However, it can be inferred that these series moved together in the long run or shared the same stochastic trend.

Since these series are found to be associated in the long run, then it becomes necessary to determine their long-run equilibrium using restricted VAR/VECM.

Table 3: Multivariate Johansen Co-integration Test

H0	H1	Statistics	Critical Value (5%)	Prob.**
		Trace Statistic		
r = 0	r ≥ 1	127.84*	47.21	
r ≤ 1	r ≥ 2	68.60*	29.68	
r ≤ 2	r ≥ 3	21.24*	15.41	
r ≤ 3	r = 4	2.06	3.76	
		Maximum Statistic		
r = 0	r ≥ 1	59.24*	27.07	
r ≤ 1	r ≥ 2	47.36*	20.97	
r ≤ 2	r ≥ 3	19.19*	14.07	
r ≤ 3	r = 4	2.06	3.76	

Source: STATA Computer printout
Note:*denotes rejection of the null hypothesis at 5 per cent level of significance

Pair-wise Co-integration Test

Results of pair-wise co-integration that was also performed across the four-variable series are given in Table 4. These tests showed that each pair, *viz*., GDP–Agriculture, GDP– Industry, Agriculture-Industry and Industry-Services had one co-integrating equation, implying that these pairs are co-integrated; there exists long-run association between them. On the other hand, the pairs: GDP- Services and Agriculture-Services had no co-integrating vector, implying non-existence of any co-integration between them, thus, no long-run association exists between this pairs. Furthermore, the non-existence of co-integration between GDP-Services indicates that most of the incomes from services are not accounted for which may be attributed to existence of numerous underground economy activities which pervades in the country. Therefore, holistic mechanism/approach by the government and attitudinal change by individuals are encouraged, in order to have a robust economy.

Table 4: Pair-wise Co-integration

Pair	H0	H1	Trace Stat	C.V (5%)	Max Stat	C.V (5%)	CE
GDP-AGR	r = 0	r ≥ 1	27.10*	20.04	22.27*	18.63	1 CE
	r ≤ 1	r =2	4.81	6.65	4.81	6.65	
GDP-IND	r = 0	r ≥ 1	21.83*	15.41	18.99*	14.07	1 CE
	r ≤ 1	r =2	2.84	3.76	2.84	3.76	
GDP-SER	r = 0	r ≥ 1	11.59	15.41	8.79	14.07	NONE
	r ≤ 1	r =2	2.79	3.76	2.79	3.76	
AGR-IND	r = 0	r ≥ 1	26.30*	20.04	21.84*	18.63	1 CE
	r ≤ 1	r =2	4.46	6.65	4.46	6.65	
AGR-SER	r = 0	r ≥ 1	14.04	15.41	10.36	14.07	NONE
	r ≤ 1	r =2	3.69	3.76	3.69	3.76	
IND-SER	r = 0	r ≥ 1	17.01*	15.41	14.98*	14.07	1 CE
	r ≤ 1	r =2	2.03	3.76	2.03	3.76	

Source: STATA Computer printout
Note:*denotes rejection of the null hypothesis at 5 per cent level of significance

Vector Error Correction Model

Having determined that there exist co-integration between aggregated income (GDP) and disaggregated incomes' (sectors) series, we then estimate the parameters of multivariate co-integration VECM for these four series. Table () contains ECT and short-run parameters estimates, along with their standard errors, z statistics, and confidence intervals. The coefficient of ECT is the parameter in the adjustment matrix for this model. Overall, the output indicates that the model fits well. The coefficient in the co-integrating equation is statistically significant and has the correct sign, imply rapid adjustment toward equilibrium. Since the prediction from the co-integrating equation is negative, it means aggregated income (GDP) is below its equilibrium value.

However, the error correction term indicates the speed of adjustment among the variables before converging to equilibrium in the dynamic model with the coefficient showing how quickly these variables return back to equilibrium.

The significant of the ECT coefficient indicates the existence of long run equilibrium between aggregated income (GDP) and disaggregated incomes (sectors), i.e. a long run causality running from aggregated income (GDP) to disaggregated incomes (sector).

Result clearly show that any disturbance in the aggregated income (GDP) in the long-run by any of the short runs (disaggregated incomes) will get corrected in about 3 months as indicated by the level of significance and the rapid speed of adjustment.

This means that distortion caused to the aggregated income (GDP) in the long-run by any of the short runs (disaggregated incomes), will make aggregated income (GDP) to adjust from displacement equilibrium to equilibrium at the speed of 24 percent, i.e. aggregated income (GDP) will take approximately 3 months to restore back to the equilibrium in the long run. In the short run, GDP was influenced by one and two years lag with respect to its own aggregate income, industry income, agriculture income; and influenced by one year lagged services income.

Table 5: Vector Error Correction Model

Variable	**Coefficient**	**S.E**	**T-stat**
ECT	-0.238	0.0497	-5.48***
D(GDP(-1))	0.271	0.055	4.91***
D(GDP(-2))	0.359	0.107	3.37***
D(AGR(-1))	-0.78	0.136	-5.74***
D(AGR(-2))	-0.69	0.339	-2.04**
D(IND(-1))	-0.682	0.156	-4.37***
D(IND(-2))	-0.66	0.198	-3.34***
D(SER(-1))	-0.699	0.3557	-1.97*
D(SER(-2))	0.174	0.1556	1.118^{NS}
CONS	-0.005	0.004	1.25^{NS}

Source: STATA Computer printout
Note: ***’ **’ * signifies significance at 1%; 5% and 10% probability levels, respectively.

Granger Causality Test

After finding pair wise co-integration among these series, granger causality was also estimated between the selected pairs. The granger causality shows the direction of income/revenue formation between pair, i.e., movement of the revenue to adjust the income difference.

Results of granger causality tests show that all the four F-statistics for the causality tests of aggregated income (GDP) on the disaggregated incomes (sectors), and vice versa were statistically significant (Table 6).

Therefore, null hypothesis of no granger causality were rejected in each of the cases. From results of granger causality test, it was observed that only bidirectional causalities exit between pairs: Agriculture-GDP, Industry-GDP, Services-GDP, Agriculture-Industry, Services-Agriculture and Industry-Services. In these cases, the former in each pair granger causes the income/revenue formation in the later which in turn provides the feedback to the former as well.

International Journal of Innovative Research and Review ISSN: 2347 – 4424 (Online)
An Online International Journal Available at http://www.cibtech.org/jirr.htm
2016 Vol. 4 (2) April-June, pp.40-53/Singh et al.
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Table 6: Pair-wise Granger Causality

Null Hypothesis	F-Stat	Prob.	Granger Cause	Direction
Agriculture does not Granger cause GDP	8.06	0.011**	Yes	Bidirectional
GDP does not Granger cause Agriculture	34.18	0.0001**	Yes	
Industry does not Granger cause GDP	12.45	0.0034**	Yes	Bidirectional
GDP does not Granger cause Industry	15.11	0.002**	Yes	
Services does not Granger cause GDP	5.03	0.036**	Yes	Bidirectional
GDP does not Granger cause Services	28.79	0.0001**	Yes	
Agriculture does not Granger cause Industry	7.85	0.012**	Yes	Bidirectional
Industry does not Granger cause Agriculture	16.22	0.002**	Yes	
Services does not Granger cause Agriculture	6.94	0.017**	Yes	Bidirectional
Agriculture does not Granger cause Services	21.45	0.001**	Yes	
Industry does not Granger cause Services	14.07	0.002**	Yes	Bidirectional
Services does not Granger cause Industry	4.99	0.04**	Yes	

Source: STATA Computer printout
Note:*denotes rejection of the null hypothesis at 5 per cent level of significance

Impulse–Response Functions

With a model considered acceptably well specified, we estimated the impulse response functions. Whereas IRFs from a stationary unrestricted VAR die out over time, IRFs from a restricted VAR (VECM) do not always die out. Because each variable in a stationary unrestricted VAR has a time invariant mean and finite, time-invariant variance, the effect of a shock to any one of these variables must die out so that the variable can revert to its mean. In contrast, the I(1) variables modeled in a restricted VAR (VECM) are not mean reverting, and the unit moduli in the companion matrix imply that the effects of some shocks will not die out over time. These two possibilities gave rise to new terms. When the effect of a shock dies out over time, the shock is said to be transitory. When the effect of a shock does not die out over time, the shock is said to be permanent. The graphs indicate that an orthogonalized shock to any of the sectors has a Transitory effects on GDP; implying that unexpected shocks that are local to any of the sectors *viz.* Agriculture, Industry and Services will have a transitory effects on the GDP (aggregated income) (Figure 1).

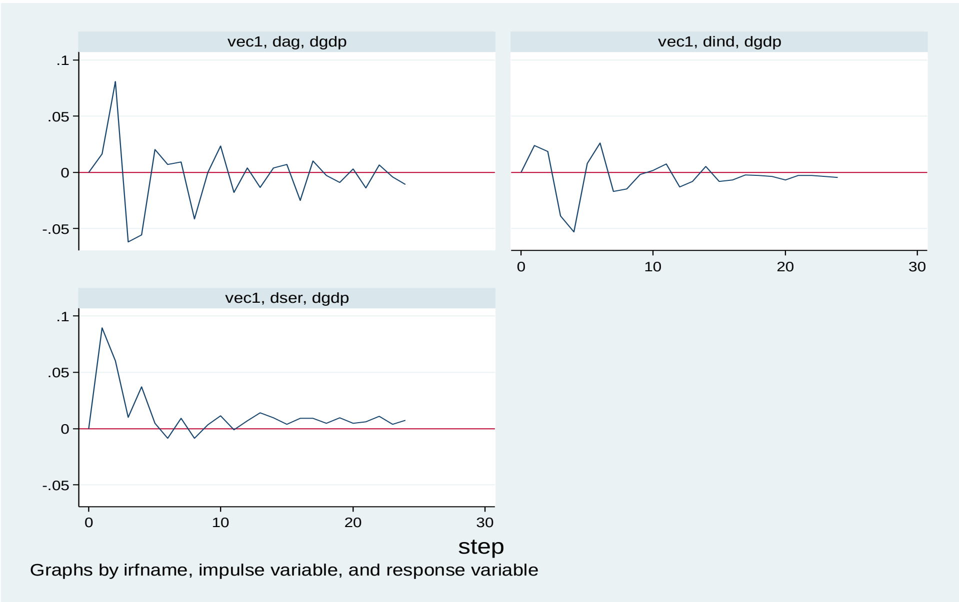

Figure 1: Impulse Response Functions

Forecasting Using VECM

Co-integrating VECMs are also used to produce forecasts of both the first-differenced variables and the levels of the variables. Comparing the variances of the forecast errors of stationary unrestricted VAR with those from a restricted VAR (VECM) reveals a fundamental difference between the two models. Whereas the variances of the forecast errors for a stationary unrestricted VAR converge to a constant as the prediction horizon grows, the variances of the forecast errors for the levels of a restricted VAR (VECM) diverge with the forecast horizon (Lütkepohl, 2005). Because all the variables in the model for the first differences are stationary, the forecast errors for the dynamic forecasts of the first differences remain finite. In contrast, the forecast errors for the dynamic forecasts of the levels diverge to infinity. As expected, the widths of the confidence intervals declined with the forecast horizons (Figure 2).

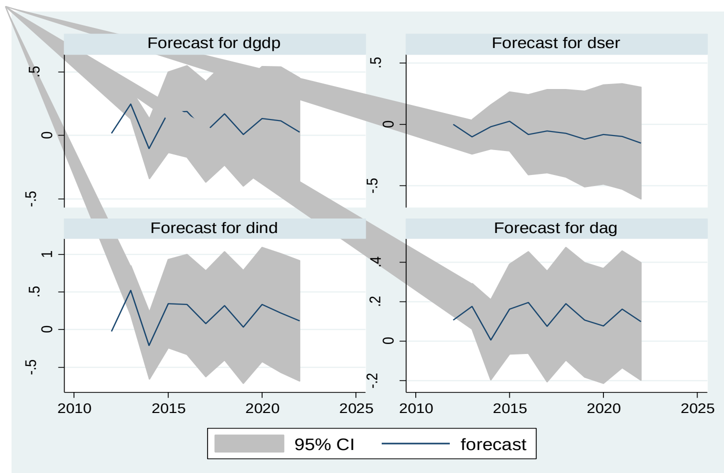

Figure 2: Forecasting Using Vector Error Correction Model

Diagnostic Checking

1. *Normality Test:* The results of normality tests indicate that the residuals are normally distributed, thus, we reject the null hypothesis of non-normally distributed errors, and accept the alternative hypothesis, because they are both skewed and kurtotic (Table 7a).

Table 7a: Test for Normality

Test	**Chi2**	**df**	**Prob. > Chi2**
Jarque-Bera Test	6.36	8	0.61
Skewness Test	4.28	4	0.37
Kurtosis Test	2.08	4	0.72

H_0: Residuals are not normally distributed
H_1: Residuals are normally distributed

2. *Autocorrelation Test*: The lag range multiplier test result of autocorrelation clearly indicates no serial correlation in the residuals. Therefore, the null hypothesis of no serial correlation at lag order is accepted, while the alternative hypothesis is rejected (Table 7b).

Table 7b: Lag Range-Multiplier Test

Lag	**Chi^2**	**df**	**Prob > Chi^2**
1	11.74	16	0.76
2	21.27	16	0.17

H0: No Autocorrelation at lag order
H0: Autocorrelation at lag order

3. *Stability Test*: The graph of the eigen values shows that none of the remaining Eigen-values appears close to the unit circle, implying that the stability check does not indicate that the model is misspecified. In other words, it means that the specified equation has no structural break. Therefore, the null hypothesis of no stability of the model is rejected, while the alternative hypothesis is accepted (Figure 3).

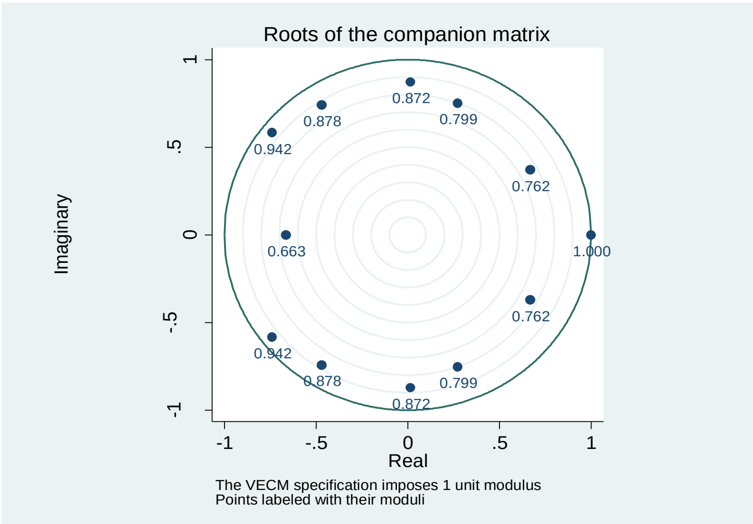

Figure 3: Stability Test

Absolute Forecast Values of GDP and the Sectors (ARIMA Forecast)

In this present work, possible ARIMA (p,d,q) models were tested and compared to each other. Among all possible models, ARIMA (1,1,1) was selected as optimal and most appropriate model based on model selection criteria such as minimum values of RMSE, MAPE, MAE, Normalized BIC and high R-squared value (Table 8a). A perusal of the ARIMA (1,1,1) result in Table 8b showed a high R^2 value, and a non-significant Q-statistic (P> 0.05), implying no autocorrelation. However, according to Maddala and Lahiri 2013, time series usually have strong trends and seasonal, hence, the R- square is normally high making it difficult to judge the usefulness of a model by just looking at the high R-square.

Table 8a: Diagnostic Checking of ARIMA Models

Variable		**ARIMA (1,1,1)**	**ARIMA (1,0,1)**	**ARIMA (1,1,0)**
GDP	SBIC	11.43*	14.01	12.06
	Ljung-Box Q-stat	0.551**	0.999	0.607
	R^2	0.96	0.63	0.94
Agriculture	SBIC	9.75*	13.98	9.97
	Ljung-Box Q-stat	0.73**	1.00	0.897
	R^2	0.96	0.63	0.94
Industry	SBIC	14.27*	15.49	14.47
	Ljung-Box Q-stat	0.77**	0.89	0.13
	R^2	0.96	0.63	0.94
Services	SBIC	9.55*	12.80	9.86
	Ljung-Box Q-stat	0.75**	1.00	0.53
	R^2	0.96	0.63	0.94

Source: SPSS 20 Computer printout
Note:*denotes the best ARIMA model
Note: **denotes rejection of the null hypothesis if P<0.05 per cent level of significance

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Furthermore, a perusal of Table 8b reveals that in all the series data, RMAPE are less than 10 percent, indicating the accuracy of the models used in this study.

Table 8b: Validation of the Models

Variable	MAPE	RMSPE	RMAPE (%)
GDP	92.96	26.77	1.9
Agriculture	75.54	3.51	2.0
Industry	723.01	337.93	6.0
Services	44.70	1.36	1.9

Forecasting with respect to GDP; Agriculture, Industry and services sectors of Nigeria from year 2013 to 2023 were done using ARIMA (1,1,1), i.e., one step ahead out of sample forecast *viz.* GDP, Agriculture, Industry and Services sectors during the period 2013 to 2023 were computed, keeping five years preceding data for validation (Table 8c and Figure 4). Predicted values with 95% Upper control limits (UCL) and Lower control limits (LCL) were also shown. From the forecasted values, it can be concluded that GDP; Agriculture, Industry and Services sectors for the few coming years (11 years) will observe an increasing trends. The forecasted values (predicted values) termed shadow prices, which reflect the true value of factor of production, can only prevail under a perfect market condition. Since forecasted/predicted values are not realistic due to market imperfection, hence estimation of upper and lower boundary, in which we expect the values not to go above or below the boundary for the coming eleven years. In other words, the upper and lower boundary values indicates, our expectation of GDP; Agriculture; Industry and Services not to exceed upper boundary or fall below the lower boundary as the case maybe for the coming eleven years. These projections can play vital role to deal with future economic measures and planning for policy makers in Nigeria. Finally, increasing agriculture funding, minimization of underground economic activities and enhancing relationship *viz.* agricultural, industrial and services sectors are important in sustaining these trends for long term.

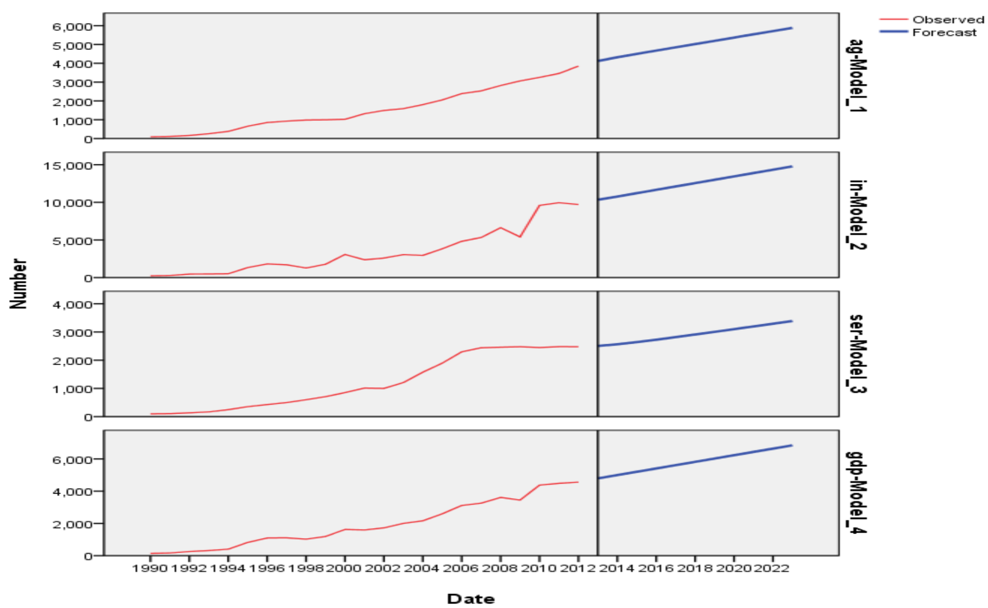

Figure 4: Forecasts of GDP-Agriculture-Industry-Services with Control Limit

Conclusion and Recommendations

This research examined progress and prospect of Nigeria economy viz. co-integration of GDP and the major sectors of the country. The results of overall co-integration test indicated the country GDP to be well-integrated with the sectors and have long-run association across them. However, pair-wise co-integration test confirmed that the pair of GDP-Services sector does not have any association between them. Furthermore, Granger causality tests revealed a causal relationship *viz.* GDP; Agriculture; Industry and Services sectors respectively, implying causality direction on revenue/income formation between them. Also, results of impulse response functions, confirmed that the speed as well as magnitude of a shock given to these sectors are relatively less transmitted to GDP, thus, revealing that Agricultural and Industrial sectors are trend followers and not trend setters. For future forecast, ARIMA (1,1,0) was found as most appropriate among other ARIMA models and employed in forecasting GDP, Agriculture, Industry and Services incomes. From the forecasted values, it can be concluded that GDP; Agriculture, Industry and Services sectors in eleven years (2013-2023) to come will observe an increasing trends. These projections can play vital role to deal with future economic measures and planning for policy makers in Nigeria. Finally, increasing agriculture funding, minimization of underground economic activities and enhancing relationship *viz.* agricultural, industrial and services sectors are important in sustaining the economic growth trend for long term.

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International Journal of Innovative Research and Review ISSN: 2347 – 4424 (Online)
An Online International Journal Available at http://www.cibtech.org/jirr.htm
2016 Vol. 4 (2) April-June, pp.40-53/Singh et al.
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APPENDIX

Forecasts of GDP-Agriculture-Industry-Services with control limit (Million Naira)

Year	**GDP**				**AGRICULTURE**				**INDUSTRY**			
	Actual	**Predicted**	**UCL**	**LCL**	**Actual**	**Predicted**	**UCL**	**LCL**	**Actual**	**Predicted**	**UCL**	**LCL**
2008	3614.44	3443.11	3957.45	2928.76	2818.53	2681.17	2900.73	2461.61	6633.59	5694.48	7827.94	3561.03
2009	3448.54	3770.26	4284.61	3255.92	3063.90	3049.51	3269.07	2829.96	5399.20	6728.73	8862.19	4595.28
2010	4377.60	3741.76	4256.11	3227.42	3249.69	3258.99	3478.54	3039.43	9605.23	6407.28	8540.74	4273.83
2011	4485.59	4408.76	4923.1	38894.41	3458.87	3423.99	3643.55	3204.44	9950.64	8738.31	10871.77	6604.86
2012	4561.20	4658.68	5173.02	4144.33	3849.10	3648.72	3868.28	3429.17	9709.80	10114.6	12248.05	7981.15
2013		4792.14	5306.49	4277.8		4121.93	4341.45	3902.37		10351.56	12485.01	8218.1
2014		4999.08	5632.15	4366.01		4321.23	4712.76	3929.7		10769.64	13273.57	8265.71
2015		5204.55	5932.95	4476.16		4501.08	5027.49	3974.68		11219.36	14101.43	8337.29
2016		5409.94	6222.32	4597.56		4675.79	5313.05	4038.52		11664.6	14873.38	8455.82
2017		5615.32	6503.77	4726.88		4849.13	5581.6	4116.66		12110.48	15616.58	8604.37
2018		5820.7	6779.19	4862.21		5022.11	5838.99	4205.23		12556.26	16336.26	8776.27
2019		6026.08	7049.84	5002.32		5194.99	6088.39	4301.59		13002.06	17037.41	8966.71
2020		6231.46	7316.57	5146.36		5367.86	6331.73	4403.98		13447.86	17723.34	9172.38
2021		6436.84	7580.01	5293.68		5540.71	6570.26	4511.16		13893.66	18396.48	9390.83
2022		6642.22	7840.64	5443.81		5713.56	6804.84	4622.29		14339.46	19058.69	9620.23
2023		6847.6	8098.83	5596.38		5886.41	7036.1	4736.72		14785.25	19711.39	9859.12

Year	**SERVICES**			
	Actual	**Predicted**	**UCL**	**LCL**
2008	2461.57	2530.92	2729.7	2332.15
2009	2477.29	2503.17	2701.94	2304.39
2010	2448.61	2525.21	2723.98	2326.44
2011	2481.50	2462.31	2661.08	2263.54
2012	2477.10	2547.96	2746.74	2349.19
2013		2504.92	2703.7	2306.15
2014		2564.69	2963.78	2165.59
2015		2641.45	3224.1	2058.81
2016		2727.28	3473.51	1981.04
2017		2817.92	3709.81	1926.02
2018		2911.13	3933.77	1888.48
2019		3005.7	4146.96	1864.45
2020		3101	4351.02	1850.99
2021		3196.69	4547.41	1845.98
2022		3292.59	4737.35	1847.84
2023		3388.6	4921.8	1855.39

Source: SPSS 20 Computer printout