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#### DISCOURSE FOR NIGERIA GREEN ALTERNATIVE

\*<sup>1</sup>Sadiq, M. S., <sup>2</sup>Singh, I. P., <sup>3</sup>Lawal, M. and <sup>1</sup>Yusuf, T. L.

<sup>1</sup>Department of Agricultural Economics and Extension Techn., Federal University of Technology, Minna, Nigeria
<sup>2</sup>Department of Agricultural Economics, SKRAU, Bikaner, India
<sup>3</sup>Department of Agricultural Education, Federal College of Education, Katsina, Nigeria Correspondence author's email: sadiqsanusi30@gmail.com
Phone number: +23470376900123

#### ABSTRACT

This study is an investigation of the future outlook of Nigerian agricultural sector's growth in the light of global financial developments using linear and symmetric price transmission mechanism model (ECM). The study makes use of annual time series data covering GDP-Agriculture and its sub-sectors which spanned from 1990-2012. The findings show that long-run association exits between agriculture and its sub-sectors with the main sector establishing long-run equilibrium with its sub-sectors, though the convergence rate was moderate as indicated by the attractor coefficient. Furthermore, results show that all the sub-sectors have positive influence on GDP-Agriculture with crop sub-sector having a lead influence when compared to other sub-sectors. Therefore, the study recommends that government should adopt adjustment strategies that hinges on shoring-up gross agriculture revenue to compensate for the dwindling oil revenues given that the prospect for the country economy depends on the policies articulated for the medium-to-long term and the seriousness with which they are implemented.

Keywords: Agriculture; Economy; Growth; ECM; ARIMA; Nigeria

#### **INTRODUCTION**

The economic aspirations of Nigerians have remained that of altering the structure of production and consumption patterns, diversifying the economic base and reducing reliance on oil. These aimed at putting the economy on thepart of sustainable, all-inclusive and non-inflationary growth. The implication 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 economy structure is expected to change as growth progresses.



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Since 1999, the economic growth of Nigeria has risen substantially, with annual average of 7.4 percent in the last decade. However, the growth has not been inclusive, broad-based and transformational. The implication of this trend is that economic growth in Nigeria has not resulted in the desired structural changes that would make agriculture the engine of growth, create employment, promote technological development and induce poverty alleviation. The economy has been import dependent with very little non-oil exports: it relies heavily on crude oil and gas exports with other sectors trailing far behind. The crude oil accounts for about 90 per cent of foreign exchange earned by the country while non-oil exports account for the balance. In recent times, the economy has been susceptible to shocks in the oil industry which have been caused by either developments in the international crude oil market or the restiveness in the Niger Delta region of the country. Agriculture which was the major economy driver before the era of black gold or oil boom has been abandoned to the rural poor. Government expenditure outlays that are dependent on oil revenues have more or less dictated the pace of growth of the economy. Looking back, it is clear that the economy has not actually performed to its full potential, particularly in the face of its rising population. Therefore, this study aims at investigating the future outlook of agricultural sector in the face of dwindling oil revenue.

#### **RESEARCH METHODOLOGY**

The present study used deflated price annual time series data covering Agriculture sector, crop, livestock, fishery and forestry sub-sectors spanning from 1990-2012, sourced from CBN database. The data were synthesized using simple regression model, ADF unit root, Elliot-Rothenberg-Stock (ERS) ADF-GLS test, and linear and symmetric price mechanism model (ECM). The empirical models used are given below:

#### Simple regression and Engel-Granger error correction model (ECM)

Consider a multivariate co-integration model as follows:

 $GDP = \pi_0 + \pi_1 Agriculture + \pi_2 Industry + \pi_3 Services + \varepsilon_t$ 



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Where;

GDP = Gross Domestic Product

 $\pi_0 = intercept$ 

 $\pi_{1-3} = \text{coefficient}$ 

 $\varepsilon_t$  = pure random walk

Co-integration of the multiple variables can be tested if all the variables display the same order of integration. The revenue adjustment mechanism between these variables, measured by Equation (1), was estimated through the Ordinary Least Squares (OLS) approach. ADF unit root test was applied to the residual of the estimation. These variables are said to be co-integrated if their residual is stationary, suggesting that there is a revenue adjustment mechanism between these multivariate series, which makes them converge to their long-term equilibrium relationship. In addition, short-term integration tests enable checking whether revenue responses on the variables are instantaneous. The short-term relationship is derived from the Granger (1981) representation theorem in the form of an ECM and is presented as follow:

 $\Delta GDP = \alpha_0 + \alpha_1 \Delta A griculture + \alpha_2 \Delta industry + \alpha_3 \Delta Services + \alpha_4 \varepsilon_{t-1} + V_t$ (1)

Where;

 $\Delta =$  First difference

 $\alpha_0 = intercept$ 

 $\alpha_{1-4} = \text{coefficient of variable}$ 

 $\varepsilon_{t-1} =$ lagged value of the residual derived from Equation (1); and,

 $V_t$  = white noise

#### **Augmented Dickey Fuller Test**

The Augmented Dickey-Fuller test (ADF) is the test for the unit root in a time series sample (Blay *et al.*, 2015; Singh, *et al.*, 2016; Sadiq *et al.*, 2016a). The autoregressive formulation of the ADF test with a trend term as cited by Beag and Singla (2014); Mahalle *et al.* (2015) is given below:

 $\Delta p_t = \alpha + p_{t-1} + \sum_{j=2}^{it} \beta i \Delta p_{it-j+t} + \boldsymbol{\mathcal{E}}$ 

(2)



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Where,  $p_{it}$  is the price in market *i* at the time *t*,  $\Delta p_{it} (p_{it} - p_{t-1})$  and  $\alpha$  is the intercept or trend term.

#### Autoregressive Integrated Moving Average (ARIMA) Model

A generalization of the ARMA models which incorporates a wide class of non-stationary timeseries is obtained by introducing the differencing into the model. The simplest example of a nonstationary process which reduces to a stationary one after differencing is Random Walk. A process  $\{y_t\}$  is said to follow an integrated ARMA model, denoted by ARIMA (p, d, q), if  $\nabla^d y_t = (1-\beta)^d \mathcal{E}_t$ is ARMA (p, q), and the model is written below (Lama *et al.*, 2015; Sadiq *et al.*, 2016b):  $\varphi(\beta) (1-\beta)^d y_t = \theta(\beta) \mathcal{E}_t$  (3)

Where,  $\mathcal{E}t \sim WN(0, \sigma^2)$ , and WN indicates white noise. The integration parameter d is a non-negative integer. When d = 0, ARIMA (p, d, q) = ARMA(p, q).

#### **Forecasting Accuracy**

For measuring the accuracy in fitted time series model, mean absolute prediction error (MAPE), relative mean square prediction error (RMSPE), relative mean absolute prediction error (RMAPE) (Paul, 2014) and  $R^2$  were computed using the following formulae:

$$MAPE = 1/T \sum (A_t - F_t)$$
(4)

RMPSE = 
$$1/T \sum [(A_t - F_t)^2 / A_t]$$
 (5)

$$RMAPE = 1/T \sum [(A_t - F_t)/A_t] \times 100$$
(6)

$$\mathbf{R}^{2} = \frac{\sum_{i=1}^{n} (A_{t} - F_{t})^{2}}{\sum_{i=1}^{n} (A_{t})^{2}}$$
(Sadiq *et al.*, 2017) (7)

Where,  $\mathbf{R}^2$  = coefficient of multiple determination,  $A_t$  = Actual value;  $F_t$  = Future value, and T = time period(s)

#### **RESULTS AND DISCUSSION**

#### Estimates of long-run effects using simple regression model (Equation 1)

The regression of a non-stationary time series variables may cause a nonsense regression as evidenced by the coefficient of multiple determination  $R^2$  (0.998) which is greater than Durbin-Watson statistic (0.794) as shown in Table 1a. A nonsense regression is not desirable given that it



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is not ideal for policy making and cannot be used for long-run prediction. However, the residuals of the simple regression (Equation 1) was found to be stationary at level as indicated by the ADF  $\tau$ -statistics in absolute term which was greater than the Engel-Granger critical value at 5% significance level (Table 1b). This implies that the variables are co-integrated and the double logarithm OLS regression is not spurious, thus, a long-run model which can be use for policy making and also ideal for policy making. In addition, the stationarity of the residual variable implies that these variables have long-run association or they move together in the long-run: shared one stochastic trend. A further perusal of Table 1a indicates that all the stimulus variables or agricultural sub-sectors included in the model viz. crop, livestock, fishery and forestry subsectors have positive influence on the total agricultural revenue of the country in the long-run. For long-run prediction, it implies that 100 percent increase in the revenues that accrue to these agricultural sub-sectors viz. crop, livestock, fishery and forestry sub-sectors will increase the country total agricultural revenue by 88.3, 6.5, 4.1 and 1.1%, respectively. Therefore, it can be inferred that the crop sub-sector will have a dominant effect on the total agricultural revenue formulation, with the sub-sector being trailed from far by the livestock and fishery sub-sectors; while forestry trailed behind with a dismal performance.

Variable	Coefficient	Standard error	t-value	
Intercept	0.21	0.031	6.774***	
Crop	0.883	0.0052	169.91***	
Livestocks	0.065	0.0061	10.73***	
Fishery	0.041	0.0033	12.39***	
Forestry	0.011	0.0031	34.68***	
R <sup>2</sup>	0.998			
R <sup>2</sup> -Adjusted	0.991			
D-W stat	0.794			
AIC	-13.302			
SIC	-13.105			
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Table 1a: Results of simple regression showing long-run effects

Note: \*\*\*, \*\*, \* significance at 1, 5 and 10% levels respectively



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#### **Table 1b:** ADF unit root test on residual

	v statistic		ger critical value	Decision
		5%	10%	
Residual (U)	-3.36*	-3.34	-3.04	Stationary at level I(0)

Note: \* indicate that unit root at the level was rejected at 5% significant level

#### Estimates of short-run effects using Error correction model (ECM)

The basic idea of co-integration was to identify the long-run relationship between variables. If there was a long-run relationship between the variables, then divergence from the long-run equilibrium path is bounded. If variables are found to be co-integrated we can specify an error correction model and estimate it using standard methods and diagnostic test. Also, since these variables were found to be integrated in the long-run i.e there is co-movement or long-run association between these variables, they are likely to establish long run equilibrium, thus, the need to develop a short-run model which capture both the long-run and short-run equilibriums. The results of the ERS (Elliot-Rothenberg-Stock) unit root test applied to the logarithm transformed variables at level shows that all the variables have unit root as indicated by the estimated tstatistics values in absolute term which were lower than their respective t-critical values at 5% confidence level, thus, accepting the null-hypothesis of non-stationarity and rejecting the alternative hypothesis of non-presence of unit root. Furthermore, the results of the ERS unit root test applied to all the variables at first difference shows all the variables to be devoid of unit root as indicated by the estimated t-statistic values in absolute term which were higher that their respective t-critical value at 5% confidence level, thus, rejecting null hypothesis of non-stationarity in favour of the alternative hypothesis of non-presence of unit root (stationary) (Table 2a). Therefore, it implies that these variables were integrated of order one I(1), thus justifying the application of Error Correction Model (ECM). However, it is worth to mention that the reason for the application of the ERS (Elliot-Rothenberg-Stock) test also termed ADF-GLS test against the ADF test which is the most widely and commonly used unit root test was due to Type II error inherent in the estimated ADF test results (though not reported in the Table) which clearly showed that the ADF test had lost its power to test for stationarity due to the presence of structural points (SAP and post-



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SAP periods) in the captured data. Because of the tendency of ADF to lose its power to test for stationarity, Maddalla and Kim (1998) as cited by Gujarati *et al.*(2012), Maddalla and Lahiri (2013) advocated that all the traditional unit root test models (DF, ADF and PP tests) should be discarded in order to avoid the problem of Type I and II errors.

The results of the short-run model which capture both the long-run and short run equilibrium is shown in Table 2b. The attractor coefficient termed the error correction term (ECT) of the Agriculture revenue (Total) against the agricultural sub-sectors was found to be significant and negatively signed, implying that the GDP-Agriculture established a long-run equilibrium with all the agriculture sub-sectors. The attractor coefficient is above the long-run equilibrium and tends to move towards the level of the sub-sectors in order to re-establish equilibrium. The estimated attractor coefficient was -0.489, indicating that the GDP-Agriculture absorbed 48.9 percent of the shocks in order to maintain a long-run equilibrium annually. It can be inferred that the GDP-Agriculture corrects its previous error from the long-run equilibrium due to any short-run equilibrium at the speed of 48.9 percent per annum i.e it adjust at the speed of 48.9% from disequilibrium to equilibrium in the long-run, which will take approximately 6 months and 26 days to re-establish long-run equilibrium with its sub-sectors. Therefore, it can be inferred that there was long-run causality running from agricultural sub-sectors jointly to the GDP-Agriculture. The results showed that the speed of convergence of the GDP-Agriculture towards the long-run equilibrium with its sub-sectors was moderate, and this can be attributed to partial efficiency of the agricultural programmes in the country i.e policy inconsistency, bureaucratic delay, poor programme implementation, corruption etc. The results of the short-run equilibrium show that each of the sub-sectors viz. crop, livestock, fishery and forestry have short-run causal effect on the GDP-Agriculture. In other words, the crop, livestock, fishery and forestry sub-sectors positively influence the total revenue that accrues to agriculture sector (GDP-Agriculture) in the short-run. Therefore, a 100 percent increase in the revenue that accrues to crop, livestock, fishery and forestry sub-sectors will increase the total GDP-Agriculture by 88.5, 6.4, 4.0 and 1.1%, respectively (Table 2b). An important observation from this study is that the long-run and short run



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elasticities were the same. In the light of the recent macroeconomic challenges, government should adopt adjustment strategies that hinges on increasing non-oil revenues to compensate for the dwindling oil revenues because agricultural revenues can stand as the main driver of economic growth over the short-medium-long term.

Variables	t_statistics	Critical value (5%)	
v allables	t-statistics	Critical value (570)	
Ln(Agriculture)	-0.813	-3.19	Non-stationary I(0)
$\Delta$ Ln(Agriculture)	-3.72		Stationary I(1)
Ln(Crop)	-0.80	-3.19	Non-stationary I(0)
$\Delta Ln(Crop)$	-3.74		Stationary I(1)
Ln(Livestocks)	-1.14	-3.19	Non-stationary I(0)
$\Delta$ Ln(Livestocks)	-3.45		Stationary I(1)
Ln(Fishery)	-1.13	-3.19	Non-stationary I(0)
$\Delta$ Ln(Fishery)	-3.81		Stationary I(1)
Ln(Forestry)	-0.56	-1.96	Non-stationary I(0)
$\Delta Ln(Forestry)$	-1.974		Stationary I(1)

Table 2a: Unit root tests

Note: \* indicate that unit root at the level or  $1^{st}$  difference was rejected at 5% significance  $\Delta$  :  $1^{st}$  difference

**Table 2b**: Results of ECM showing short-run effects

Variable	Coefficient	Standard error	t-value
Intercept	0.124	0.111	1.117 <sup>NS</sup>
$\Delta Ln(Crop)$	0.885	0.0041	217.39***
$\Delta$ Ln(Livestocks)	0.064	0.0051	12.51***
$\Delta$ Ln(Fishery)	0.040	0.0029	13.92***
$\Delta Ln$ (Forestry)	0.011	0.0006	18.85***
ECT <sub>t-1</sub>	-0.489	0.2453	-1.993*
$\mathbb{R}^2$	0.9999		
R <sup>2</sup> -Adjusted	0.9993		
AIC	-13.64		
SIC	-13.39		
HIC	-13.58		

Note: \*\*\*, \*\*, \* significant at 1%, 5% and 10% levels respectively NS: non-significant

#### **Diagnostic Testing**

Table 2c shows the diagnostic statistics results of the ECM model. The test of autocorrelation showed that the residuals were not serially correlated as indicated by the Breusch-Godfrey



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Lagrange Multiplier (LM) statistic which was not different from zero at 10% significance level (p>0.10). The Arch test results revealed that the variance of the current residuals and that of the lagged residuals do not correlate as indicated by the Q-statistic which was not different from zero at 10% significance level (p>0.10), thus the acceptance of null hypothesis of no Arch effect. The stability test depicted in Figure 1 show that the cusum line was within the boundary of 5% significance level, implying that there was no structural break in the equation: the models was not misspecified. Furthermore, the result of the normality test showed that the residuals were normally distributed as indicated by Jarque-Bera statistic which was not different from zero at 10% significance level (p<0.10). Therefore, based on the outcome of the diagnostic statistics, it can be inferred that the ECM model used was the best fit and valid for prediction.

Test		Statistic	P-value
Autocorrelation	Breusch-Godfrey LM test (F-stat)	1.0442	0.5197
	Breusch-Godfrey LM test (Obs. R <sup>2</sup> )	15.726	0.2041
Arch effect	Q-stat	2.664	0.103
Normality	Jarque-Bera	1.016	0.6018



#### Figure 1: Stability test trends

#### **Forecasting Using ARIMA**

Various combinations of the ARIMA models were tried after the first differencing of each variable series, and based on the smallest AIC value the best ARIMA model was selected. Of all the



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ARIMA models tested, ARIMA (1,1,0) model proved to be the best for almost all the variables except livestock's sub-sector which proved that ARIMA (0,1,1) to be the best given that it has the lowest AIC value (Table 3a).

Variable		1,1,1	1,1,0	0,1,1
Agriculture	AIC	270.17	268.25**	268.34
	SBC	273.44	270.43	270.52
	Log likelihood	-132.08	-132.12	-132.17
Crop	AIC	271.54	269.60**	269.67
	SBC	274.81	271.78	271.85
	Log likelihood	-132.78	-132.80	-132.83
Livestock	AIC	265.36	264.18	263.49**
	SBC	268.64	266.36	265.67
	Log likelihood	-129.68	-130.09	-129.75
Fishery	AIC	267.01	265.01**	265.24
	SBC	270.28	267.19	267.42
	Log likelihood	-130.50	-130.50	-130.62
Forestry	AIC	252.85	251.91**	253.49
	SBC	256.12	254.09	255.67
	Log likelihood	-123.42	-123.95	-124.75

#### Table 3a: AIC and BIC values of different ARIMA models

Note: \*\* indicates best ARIMA

Out of the total 22 data points (1990 to 2012), the first 17 data points (from 1990 to 2007) were used for model building, while the remaining 5 data points (from 2008 to 2012) were used for



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model validation. One-step ahead forecasts of the revenue for each variable along with their corresponding standard errors using naïve approach for the period 2008 to 2012 with respect to the fitted models were computed (Table 3b).

Date	Agricultu	re	Crop		Livestock		Fishery	
	Actual	Forecast	Actual	Forecast	Actual	Forecast	Actual	Forecast
2008	2818.53	2697.14	2818.08	2696.99	2869.19	2735.02	2755.65	2609.47
2009	3063.90	3040.26	3069.44	3038.60	3065.84	3114.02	2963.09	2962.29
2010	3249.69	3269.07	3254.01	3276.29	3267.52	3206.97	3157.01	3143.70
2011	3458.87	3428.33	3459.50	3432.43	3515.29	3470.48	3391.73	3332.01
2012	3849.10	3647.93	3864.30	3646.83	3804.30	3709.30	3672.30	3583.68
Date	Forestry							
	Actual	Forecast						
2008	2760.18	2643.03						
2009	2924.85	3000.09						
2010	3095.11	3083.29						
2011	3302.65	3257.45						
2012	3489.30	3490.99						

 Table 3b: One step ahead forecasts

The forecasting ability of the selected ARIMA models of revenue series for the economic variables were judged on the basis of  $R^2$ , the mean absolute prediction error (MAPE), root mean square error (RMSE) and relative mean absolute prediction error (RMAPE) values (Table 3c). A perusal of Table 3c shows that the RMAPE of each variable is less than 5 percent, indicating the accuracy of the models used.



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Variables	ARIMA model	<b>R</b> <sup>2</sup>	MAPE	RMSPE	RMAPE (%)
Agriculture	1,1,0	0.99	71.47	3.26	2.1
Crop	1,1,0	0.99	74.84	3.62	2.21
Livestock	0,1,1	0.99	57.27	2.22	1.75
Fishery	1,1,0	0.99	61.73	2.20	1.99
Forestry	1,1,0	0.99	10.75	1.39	0.41

#### Table 3c: Validation of models

Source: Authors computation, 2017

One step ahead out of sample forecast of the revenue for the economic variables selected during the period of the year 2013 to 2024 were computed. The absolute data points are shown in Table 3d and also were depicted in Figure 2a-2e to visualize the performance of the fitted model. A cursory review shows that the revenue of each variable would be marked by an increase, which is an indication of good prospect for the country economy. Under normal growth the forecasted trend will prevail; while under high and low growth the future trend of revenues for each variable will not exceed the upper and lower confidence limits, respectively. It can be observed from the forecasted results that crop sub-sector will have the highest contribution to the country GDP-Agriculture, while the remaining sub-sectors trailing behind. Under normal growth, the forecasted annual revenue growth rate for GDP-Agriculture, crop, livestock, fishery and forestry sub-sectors will be 3.6, 3.5, 3.5 and 3.4%, respectively. In the case of high growth, the annual revenue growth rate for GDP-Agriculture, crop, livestock, fishery and forestry sub-sectors are estimated to be 4.7, 4.4, 4.6 and 5.1%, respectively; and, under low growth, the estimated revenue growth rate for GDP-Agriculture, crop, livestock, fishery and forestry will be 2.1, 2.4, 2.1 and 1.1%, respectively. Therefore, since the country anticipated growth exceed the future outlook, onus lies on the stakeholders to implement sound policies to make agricultural sector the main driver of the economy due to the low oil prices which leads to decline in fiscal revenues, vulnerability to slow global economic recovery and global financial development.



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Ta	<b>ble 3d</b> : Ou	t of sample	forecasts (1	Billion <del>N</del> )					
Date	Agriculture			Crop production	n		Livestock		
	LCI	Forecast	UCI	LCI	Forecast	UCI	LCI	Forecast	UCI
2013	3917.9934	4118.7760	4319.5585	3929.2912	4136.4551	4343.6191	3847.3379	4026.8586	4206.3793
2014	3981.8701	4334.7613	4687.6524	3991.3899	4352.1480	4712.9061	3861.4331	4195.3967	4529.3603
2015	4043.6660	4526.8345	5010.0030	4052.9330	4543.8069	5034.6808	3927.0873	4363.9347	4800.7822
2016	4112.9498	4708.2582	5303.5677	4123.0222	4725.2353	5327.4485	4012.7231	4532.4728	5052.2224
2017	4191.4752	4884.9389	5578.4025	4202.9123	4902.3091	5601.7058	4109.8732	4701.0108	5292.1485
2018	4278.5429	5059.5072	5840.4714	4291.5783	5077.5291	5863.4799	4214.7606	4869.5489	5524.3372
2019	4372.8752	5233.1347	6093.3943	4387.5721	5251.9602	6116.3482	4325.3095	5038.0869	5750.8644
2020	4473.2346	5406.3433	6339.4519	4489.5766	5426.0553	6362.5341	4440.2336	5206.6250	5973.0164
2021	4572.8752	5579.3652	6580.1458	4596.5240	5600.0075	6603.4911	4558.6707	5375.1631	6191.6554
2022	4688.0991	5752.3040	6816.5090	4707.5807	5773.8989	6840.2171	4680.0092	5543.7011	6407.3931
2023	4801.1298	5925.2059	7049.2819	4822.1006	5947.7643	7073.4281	4803.7967	5712.2392	6620.6817
2024	4917.1671	6098.0912	7279.0153	4939.5799	6121.6187	7303.6576	4929.6874	5880.7772	6831.8670
GR%	2.1	3.6	3.5	2.1	3.6	4.7	2.4	3.5	4.4
Date	Fishery			Forestry					
	LCI	Forecast	UCI	LCI	Forecast	UCI			
2013	3691.3391	3882.8504	4074.3617	3525.9392	3663.0421	3800.1450			
2014	3730.7082	4063.3432	4395.9783	3557.6694	3827.7811	4097.8927			
2015	3782.2709	4232.2369	4682.2029	3582.9825	3986.2407	4389.4988			
2016	3847.3839	4396.6544	4945.9249	3609.0039	4140.3204	4671.6369			
2017	3923.8437	4559.3446	5194.8455	3639.0569	4291.3453	4943.6338			
2018	4009.2105	4721.3682	5433.5259	3674.5355	4440.2396	5205.9436			
2019	4101.5215	4883.1345	5664.7475	3715.8481	4587.6477	5459.4473			
2020	4199.3192	5044.8016	5890.2840	3762.9036	4734.0193	5705.1349			
2021	4301.5391	5206.4304	6111.3216	3815.3718	4879.6679	5943.9640			
2022	4407.3980	5368.0444	6328.6907	3872.8224	5024.8122	6176.8021			
2023	4516.3095	5529.6526	6542.9958	3934.8002	5169.6049	6404.4096			
2024	4627.8250	5691.2587	6754.6924	4000.8630	5314.1522	6627.4414			
GR%	2.1	3.5	4.6	1.1	3.4	5.1			

LCI: Lower confidence interval; UCL: Upper confidence interval



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#### **ARIMA diagnostic Checking**

The model verification is concerned with checking the residuals of the model to see if they contained any systematic pattern which still could be removed to improve the chosen ARIMA. The results of the autocorrelation tests for each variable showed the residuals to be purely random as indicated by the Ljung-Box Q-statistics tests which were not significantly different from zero at 10% probability level. Also, the Arch effect tests showed no arch effects in the residuals as evidence by Arch-Lagrange multiplier (LM) test statistics which were not different from zero at 10% probability level. The normality tests for each variable showed that the residuals were normally distributed as evidence by Jarque-Bera test statistics which were not different from zero at 10% probability level (Table 3e). Therefore, these proved the selected model to be the best fit and appropriate model for forecasting.

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	ARIMA	Autocorrelation test	Arch test (LM)	Jarque-Bera
Variables	model	(Ljung-Box Q)		Normality test (Chi <sup>2</sup> )
Agriculture	1,1,0	0.254 (0.614) <sup>NS</sup>	7.780 (0.455) <sup>NS</sup>	1.641 (0.4402) <sup>NS</sup>
Crop	1,1,0	0.2102 (0.647) <sup>NS</sup>	4.413 (0.353) <sup>NS</sup>	1.715 (0.424) <sup>NS</sup>
Livestock	0,1,1	0.1468 (0.702) <sup>NS</sup>	1.487 (0.829) <sup>NS</sup>	1.674 (0.433) <sup>NS</sup>
Fishery	1,1,0	0.0985 (0.754) <sup>NS</sup>	1.987 (0.738) <sup>NS</sup>	0.949 (0.622) <sup>NS</sup>
Forestry	1,1,0	1.2556 (0.263) <sup>NS</sup>	2.873 (0.579) <sup>NS</sup>	3.484 (0.175) <sup>NS</sup>

<b>Table Se:</b> Diagnostic checking for best AKINIA mod
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Note: \*\*\*, \*\*, \* significance at 1, 5 and 10% respectively

NS: non-significant

(): p-value

#### CONCLUSION AND RECOMMENDATIONS

This research has investigated the future outlook of Nigerian agricultural sector growth in the light of global financial developments using linear and symmetric price transmission mechanism model. The results showed that the residual of the OLS regression was stationary at level, indicating that GDP-Agriculture and its sub-sectors were co-integrated. Furthermore, it was observed that the



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GDP-Agriculture established a long-run equilibrium with its sub-sectors, and tends to correct any error from the equilibrium caused by any shock from the short-run equilibrium at a moderate rate annually. The agriculture sub-sectors were found to exert positive influence on the GDP-Agriculture revenue formation. Also, it was observed that the future outlook of the GDP-Agriculture and its sub-sectors will witness an increasing trend with the forecasted growth rate ranging from 3.4-3.6%. Therefore, in the light of the recent macroeconomic challenges, study recommends that government should adopt adjustment strategies that hinges on increasing GDP-agriculture revenue to compensate for the dwindling oil revenues given that its sub-sectors can stand as the main driver of the economy development over the medium term.

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Row 1- Figure 2a: Agriculture; Figure 2b: Crop Row 2: Figure 2c: Livestock; Figure 2d: Fishery



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Figure 2e: Forestry