Macroeconomics and Monetary Economics

Dynamics of Agricultural Productivity in Sub-Saharan Africa: A P-ARDL Model Approach

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Abstract: This study empirically examined the long- and short-run dynamics of agricultural productivity in 37 selected countries in sub-Saharan Africa between 1990 and 2016 employing the recent Panel Auto Regressive Distributed Lag model. The model estimate revealed a cointegrating but no short-run significant relationship between agricultural output and the independent variables. The Cobb-Douglass production function thus supports long-run but not short-run estimation of agricultural production in this region during the reviewed period. The study found that labour and the real exchange rate have a positive and significant long-run influence on agricultural productivity while capital, degree of openness and per-capita income exhibit a negative but significant relationship with such productivity. The negative and significant Error Correction Term value showed that all the variables move towards long-run stability at a slow annual speed of adjustment of 29.2%; the influence of the independent variables thus enhances agricultural productivity in the long run. Based on these findings, the formulation and implementation of effective macroeconomic policies are recommended to stabilize the exchange rate, encourage exports, optimally utilize capital, and enhance infrastructure provision with a view to boosting agricultural productivity to stimulate economic growth in sub-Saharan Africa.

Keywords: Agricultural Value-Added; sub-Saharan Africa; Co-integration; Panel Auto Regression Distributed Lag Model

JEL Classification: N50

1. Introduction

The agricultural sector is the oldest and most prominent economic activity in most countries in sub-Saharan Africa (SSA) and it is thus poised to play a leading role in achieving sustainable regional development. (Bond, 1983; Diao et al., 2010; Christiaensen et al., 2011) The sector is a large employer of labour and a key

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producer of exports that stimulate economic growth. It also generates significant revenue that helps to grow the industrial sector. Indeed, scholars posit that accelerated growth results from simultaneous agricultural and industrial transformation. (Lewis, 1954; Jedwab & Vollrath, 2015; Barrett et al., 2017) However, most SSA economies have yet to achieve this goal.

As shown in figure 1 below, the SSA agricultural sector's contribution to Gross Domestic Product (GDP) growth has been waning for more than two decades. (Collier & Dercon, 2014; Hilson & McQuilken, 2014) This is partly due to the significant negative effect of Structural Adjustment Programs (SAPs), which heralded a surge in crude oil prices and inflation in the 1980s. (Mosley, 1989; Smith, 1989; Kamlongera & Hilson, 2011; Jayne & Rashid, 2013; De Vries et al., 2015) These impacts have been somewhat smoothed by the unstable but promising agricultural sector which is an important source of food products and thus contributes to reduced commodity prices. It is also a major exporter, and the domestic and foreign earnings it generates are pivotal to the growth of the region's manufacturing, industrial and service sectors. Nonetheless, in most SSA countries, SAPs hampered economic growth, especially in light of the fact that they were imposed at a time when most of these countries had gained independence. Structural adjustment programs exposed these fragile economies to global shocks. The agricultural sector was not able to generate significant capital investment and revenue and this negatively impacted the manufacturing sector, impeding economic growth. (Bond, 1983; De Vries et al., 2015)

Faced with slow economic growth and rising unemployment (IMF, 2017), SSA countries have intensified efforts to diversify their economies and agriculture is a major tool in this quest. Countries in the region have thus adopted policies that aim to boost agricultural productivity in order to ensure food security, reduce poverty and stimulate growth. (World Bank, 2007) However, while annual growth in agricultural real value added (constant 2010 US\$) in the region remained steady at about 4% from 1990 to 2013, figure 1 shows that the sector's contribution to GDP fell from about 23% in 1990 to almost 18% in 2016¹ Yu and Nin-Pratt (2011), Fuglie and Rada (2013) and Ssozi *et al.* (2017) note that, despite the slight increase in agricultural output since 1990 it remains the lowest among the global regions. This has been attributed to the different global dynamics in input growth rather than increased production.

Figures 1 illustrates fluctuating trends in agricultural productivity, both in terms of contribution to GDP and annual growth in SSA from 1990 to 2016. Agricultural productivity as share of GDP fell from 23% in 1990 to 18% in 2016 despite a slight

¹ See (Barrett et al., 2017).

improvement in the annual growth rate from less than 1% in 1990 to about 3% in 2016.

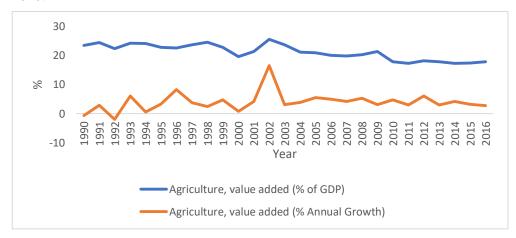


Figure 1. Trends in Agriculture growth pattern in SSA

Source: World Bank Annual Data; Authors' computation

The supply, combination and distribution of input factors such as labour, capital and land in the agricultural production process are significant in determining aggregate output. An optimal combination of these factors would result in the highest possible standard of living and maximize agricultural output while an inefficient mix reduces aggregate output and thus hampers economic growth. ¹

A literature review revealed slight improvement in agricultural output growth in SSA (as shown in figure 1) but different evaluations of the scope of such due to differences in the methodology employed.² Some studies investigated single countries such as Kenya (Owuor, 1999), Nigeria (Imahe & Alabi, 2005; Brownson et al., 2012), Ghana (Enu & Attah-Obeng, 2013), Palestine (Abugamea, 2008) and Australia (Sheng et al., 2017). Most measured growth in total factor productivity (TFP) using inputs such as land, labour and research. However, there is a paucity of empirical research on the nature and type of relationship among the dynamic factors that determine agricultural productivity in a region such as SSA. (for example, Ajao, 2011) This study filled this gap by examining the factors that determine agricultural productivity in 37 selected SSA countries from 1990 to 2016 using a Panel Auto Regressive Distribution Lag (P-ARDL) model. Premised on the theory of growth which supports the argument that the agriculture sector is a significant catalyst for economic growth, it uses the sector's share of GDP as an indicator of such

¹ See (Alvarez-Cuadrado et al., 2017).

 $^{^2}$ See (Block, 1995; Lusigi &Thirtle, 1997; Fulginiti et al., 2004; Nin Pratt & Yu, 2008; Alene, 2010; Fuglie & Rada, 2013; Akande et al., 2017).

productivity. The study's objectives were to (i) examine the determinants of agricultural productivity in SSA; (ii) determine the long- and short-run association between agricultural productivity and selected variables influencing agricultural output in this region; (iii) analyze the nature of the relationship between agricultural output and the factors influencing such output in SSA; and (iv) determine if the influence of long-run factors of production enhances agricultural output in this region.

Section 2 reviews the literature relevant to the study, while section 3 presents the methodology employed. Section 4 analyzes and interprets the empirical results and section 5 presents conclusions and policy recommendations arising from the findings. It should be noted that the selection of the SSA countries and the period covered were determined by data availability.

2. Literature Review

The SSA agricultural sector contributes more than 30% of the region's GDP and foreign exchange income. While its output growth has improved slightly since 2000, except for a dip in 2015, it trails behind other regions due to low crop production and high dependence on imports. Output growth thus requires enhanced production. (Collier & Dercon, 2014)

2.1. Empirical Review

There is a paucity of research on the determinants of agricultural productivity in the SSA region. Alene (2010) comparative study on agricultural productivity in 47 SSA countries used the contemporaneous and sequential technology of the Malmquist distance function model. The study found annual mean agricultural growth of 0.3% under the contemporary method and 1.8% using the sequential technology. It concluded that technical innovation, climatic conditions and trade significantly impact on agriculture productivity in the region. Similarly, Yu and Nin-Pratt (2011) adopted the Non-Parametric Malmquist (NPM) index to reveal a significant rebound in agricultural performance in SSA countries between 1984 and 2006 following 45 years of poor productivity, due to improved factors of production efficiency and macroeconomic policy formulation. The authors advocated for aggressive technological improvement to arrest the downward trend in agricultural growth.

Fuglie and Rada (2013) attribute on-going poverty and food insecurity in SSA to inadequate agricultural development and state that production factors such as land and labour are the key to increasing agricultural output. Using a panel data method, the study investigated the dynamic nature of the SSA agricultural sector and the importance of certain factors that impact its productivity such as research, macroeconomic policy formulation, labour, human capital, political violence and

AIDS. It found no significant improvement in aggregate agricultural production from 1961 to 1985 and only meagre improvement of 1% up until 2008. The authors suggest that governments should increase expenditure on research and development (R&D) to boost agricultural productivity.

In summary, the literature shows that, between 1960 and early 1980, the SSA agricultural sector was characterized by low productivity while the late 1980s was marked by productivity growth ranging from 0.5% to 2%, largely influenced by policy interventions, technological improvements and increased expenditure on R&D.

In examining the drivers of agricultural production in Kenya, Owuor (1999) considered the Multi-Stage Probability proportional to the size estimate approach for 1 500 selected households in 1997. The results indicated a positive relationship between non-farm income and land per crop output in the western, maize cropping area and central parts of Kenya. It pointed to the significant role played by off-farm income in boosting agricultural productivity, stressing the need for policies to be formulated with regard to commercial activities such as textile and sugar in order to increase household income.

Imahe and Alabi (2005) examined the factors affecting agricultural productivity in Nigeria using the sector's contribution to GDP and output growth as indicators while land, climatic conditions, imports, capital spending and private credit to agriculture were considered as independent variables. The regression results indicate that all the explanatory factors had a significant effect on agricultural productivity and output growth in all the models. The authors recommend more widespread irrigation, facilitating access to arable farmlands and bank credit, reduced food imports and capital investment in the agricultural sector as measures to improve sectoral productivity.

Abugamea (2008) modelled the determinants of agricultural production in Palestine using Johansen-Granger Cointegration and the Error Correction Model (ECM) to predict the long- and short-run relationships, respectively. Arable land, capital and labour were used as indicators. The study found that labour and capital have a strong, significant positive and negative relationship, respectively with output and the author advocates for reduced factor costs and enhanced labour productivity to improve agricultural production.

Ajao (2011) examined variations in agricultural productivity in SSA using Data Envelopment Analysis (DEA) between 1961 and 2003 to determine the effect of education, land typology and governance on agricultural productivity. The analysis showed that all the indicators, except government effectiveness, were significant while education and the quality of land had a negative relationship with productivity.

Brownson et al. (2012) analysed the dynamic relationship between the agricultural sector's share of GDP and certain macro-determinants in Nigeria using the ECM. The inflation rate, external reserves, exports, and debt were found to have a significant but negative association with agricultural output in both the short and long run, while the exchange rate and GDP per capita were positively significant. The authors recommended policy reforms to drive agricultural investment, diversification of the economy and promotion of the industrial sector as measures to improve agricultural output in Nigeria.

Enu and Attah-Obeng (2013) investigated the macro-determinants of agricultural production in Ghana using the Cobb-Douglas production function and Ordinary Least Squares (OLS) model. The study examined the effect of inflation, the exchange rate, income per capita and labour on agricultural output and found that a unit increase in labour reduces agricultural productivity by almost 0.66; a unit rise in inflation expands production by 0.0046; a unit increase in the exchange rate boosts production by 0.084 and a unit rise in income decreases output by 1.06. The results thus show that income per capita, the exchange rate and labour are significant factors in agricultural productivity in Ghana and the authors recommend that efforts should be made to enhance the sector's ability to promote food security.

Sheng et al. (2017) adopted the accounting approach to empirically measure capital and labour's contribution to agricultural productivity in Australia from 1949 to 2012. Using the forecasted and actual methods, the study found that capital yields higher returns than labour, indicating that varying input and output efficiencies tend to enhance agricultural productivity in the country.

Finally, Akande et al. (2017) analysed the relationship between agricultural exports and productivity in SSA countries, using stochastic regression analysis between 1981 and 2005. The scholar found that increased exports negatively impact agricultural output and advocates for policies that promote exports and institutional quality to further boost agricultural productivity.

3. Empirical Methodology

3.1. Model Specification

This study models agricultural productivity and the factors influencing it in SSA using the standard Average Production Function (APF) which depicts the relationship between agricultural inputs and output. This model is rooted in the Cobb-Douglas production function based on the Neo-Classical theory. Here, we follow the assumption that agricultural production is a function of a production function written as follows:

$$Y_t = A_t L_t^{\beta} K_t^{\alpha}, \text{ where } 0 < \alpha < 1; 0 < \beta < 1$$
 (1)

Where Y_t is the aggregate output produced at a time t, measured as the annual real value of production of total goods; A_t is the Total Factor Productivity (TFP) at time period t; L_t denotes labour measured in terms of the aggregate amount of personhours in a given time period t; K_t denotes capital as the real value of all machinery, equipment, and buildings in a particular period and t; β and α denote the respective output elasticities of labour and capital. Y_t, A_t, L_t, K_t are all constants and are a function of the prevailing available technology.

The Cobb-Douglas model is subject to constant scale of output on the condition: $\beta + \alpha = 1$. This shows that a proportionate increase in the use of capital K_t and labour L_t would produce a proportionate increase in output Y_t . Therefore, if $\beta + \alpha > 1$, it depicts an increasing scale of output while $\beta + \alpha < 1$ depicts a reducing scale of output. Suppose we express equation (1) in a linear logarithm production equation form, this is depicted as:

$$log(Y_t) = C_O + log(A_t) + \beta log(L_t) + \alpha log(K_t)$$
(2)

where Y_t , L_t and K_t represent output, labour and capital, respectively, C_0 is the constant factor and A_t is the TFP captured by the control variables. The factors used in this study are degree of openness, the real exchange rate and per-capita income. Here, we follow the assumption that TFP is a function of the degree of openness (DOPEN), real exchange rate (REXC) and per-capita income (GDPPC) over a period t shown below:

$$A_t = f(DOPEN_t, REXC_t, GDPPC_t)$$
(3)

By replacing A_t in equation (3) in equation (2), the Cobb-Douglass production function becomes:

$$Y_t = DOPEN_t^{\beta_1} REXC_t^{\beta_2} GDPPC_t^{\beta_3} L_t^{\beta} K_t^{\alpha}$$
(4)

Equation (4) depicts the agricultural productivity function model for SSA where Y_t is the agricultural output that represents the agricultural sector's contribution to GDP. In line with Kahsay and Hansen (2016, p. 56), we convert equation (4) to a log form to depict the agricultural production (AGVA) equation in a pooled data system, as shown below:

$$log(AGVA_{it}) = C_i + \beta_1 logDOPEN_{it} + \beta_2 logREXC_{it} + \beta_3 logGDPPC_{it} + \beta logL_{it} + \alpha logK_{it} + \varepsilon_{it}$$
(5)

Where $AGVA_{it}$ (Agricultural output share of GDP) is used as an indicator of Y_{it} ; C_i is the constant term; TFP $(logA_t)$ is proxied by $\beta_1 logDOPEN_{it} + \beta_2 logREXC_{it} + \beta_3 logGDPPC_{it}$; labour and capital are respectively represented by $\beta logL_{it} + \alpha logK_{it}$; i denotes a particular country and ε_{it} represents the error term. Thus, we denote the P-ARDL model in SSA below:

$$\Delta Y_{it} = \beta_{i0} + \beta_1 \Delta X_{it-1} + \beta_2 \Delta X_{it-2} + \beta_3 \Delta X_{it-3.....} + \beta_p \Delta X_{it-n} + \alpha_1 y_{it-1} + \alpha_2 y_{it-2} + \alpha_3 y_{it-3} + \cdots + \alpha_0 y_{it-r} + \varepsilon_{it}$$
(6)

Where Y_{it} is the vector of endogenous factors representing agricultural productivity; β_{i0} is the vector of the constant term; i denotes the SSA countries; Δ represents the I(1) values; and X_i and y_i are the previous period values of the independent factors, where i=1, up to the lagged nth and rth period; $\beta_1-\beta_p$ depicts the short-run relationship; $\alpha_1-\alpha_q$ represents the long-run dynamics; and ε_{it} is a vector of error terms.

3.2. Definition of Variables and Data Sources

Following Ajao (2011), this study uses annual data on 37 SSA economies from 1990 to 2016. The choice of variables mirrors those used in some existing literature based on the Cobb-Douglass production theory. The dependent variable is agricultural output represented by agriculture's contribution to GDP (AGVA), measured in % GDP, which is the net sectoral output and comprises forestry, fishing, and crop and livestock production in SSA, sourced from the World Bank Indicator (WDI) National Account data. The independent indicators adopted in the study are dynamic factors and control factors.

The factors of production are proxied by labour (LABR) and capital (CAPI). Labour (LABR) is defined by the rate of labour force participation, measured in terms of the percentage of total population aged 15 and older that is economically active and provides labour to produce goods and services in SSA. This data was sourced from the International Labour Organization's ILOSTAT database. Capital (CAPI), which refers to Gross Capital Formation at current Purchasing Power Parity (PPP), includes an increase in a country's fixed assets and net variance in the stock level in SSA, captured in the Penn World Table. (Feenstra et al., 2015) In line with Hart et al. (2015) and Almasifard and Khorasani (2017), the trade indicator is proxied by DOPEN, that is, the percentage contribution of the ratio of the total value of import and export of goods and services to GDP, which measures the level of openness of the SSA economy. This data was also sourced from the WDI National Account data.

The control variables are real exchange rate (REXC) and per-capita income (GDPPC) which is in line with Enu and Attah-Obeng (2013) and Brownson et al. (2012). Per-capita income is the annual percentage growth in GDP per capita of the selected SSA countries in constant 2010 U.S. dollars. It is measured as the ratio of GDP to midyear population and was sourced from the WDI National Account data. The real exchange rate denotes variations in the value of a country's currency at constant prices measured in terms of the product of the value of its domestic currency and the US CPI divided by the product of a dollar value and the CPI of a domestic

¹ See (Yuan, 2011; Fuglie & Rada, 2013; Bashir, 2015; Wagle, 2017).

currency. Thus appreciation of a country's exchange rate is an indication of a strengthening US dollar or a reduction in the value of the local currency. Depreciation indicates a reduction in the dollar or an increase in the value of the local currency. The data was sourced from the International Macroeconomic data set of the United States Department of Agriculture (USDA).

Sub-Saharan African countries are developing countries that are geographically located in the part of the African continent that lies south of the Sahara. Due to data constraints, 37 countries were included in the study, namely, Angola, Benin, Botswana, Burkina-Faso, Cabo Verde, Cameroon, Central African Republic, Chad, Côte d'Ivoire, Djibouti, Ethiopia, Gabon, Gambia, Ghana, Guinea, Guinea-Bissau, Kenya, Lesotho, Liberia, Madagascar, Malawi, Mali, Mauritania, Mauritius, Mozambique, Namibia, Nigeria, Republic of Congo, Rwanda, Senegal, Sierra-Leone, South Africa, Swaziland, Tanzania, Togo, Uganda and Zambia.

3.3. Estimation Technique

This research focuses on agricultural sector productivity in SSA between 1990 and 2016. The objectives are to: (i) examine the determinants of agricultural productivity in SSA; (ii) determine the long- and short-run association between agricultural productivity and selected variables influencing agricultural output in this region; (iii) analyze the nature of the relationship between agricultural output and the factors that influence such output in SSA; and (iv) determine if the influence of long-run factors of production enhances agricultural output in this region.

In determining the dynamic relationship, it is first necessary to carry-out unit root tests (stationarity/non-stationarity) and co-integration among the variables to identify the suitable methodology for our analysis. In doing so, we consider the methodological conditions highlighted by Giles (2013). For example, the Ordinary Least Square (OLS) estimation technique is appropriate when the variables are at level (I(0) and have no unit root; the Vector Auto-regression (VAR) and OLS methods are applicable when the variables are all integrated after first difference (I(1)) and there is no co-integration among them; and the OLS regression model and estimation of the ECM can be employed to ascertain the long- and short-run dynamics of the association among the variables when the variables are all integrated of the same order and are cointegrated. However, there are conditions when some of the variables could be stationary at I(0) and some at I(1) and perhaps also fractionally integrated while some of the variables integrated at I(1) could also be cointegrated. The ARDL or Bounds Testing modelling technique has been proven to be appropriate to determine the long- and short-run dynamics under the above condition. (Pesaran & Shin, 1998; Pesaran et al., 2001; Ahmad & Du, 2017) Since the variables considered in this research fit into the above situation, this study employs the P-ARDL model recently developed by Chudik and Pesaran (2013).

Following Rafindadi and Zarinah (2013), Faridi and Murtaza (2014), Bashir (2015), Asumadu-Sarkodie and Owusu (2016) and Awan and Yaseen (2017), we employ the P-ARDL methodology recently developed by Chudik and Pesaran (2013) to test for the presence of long- and short-run relationships between agricultural productivity and the factors affecting output in SSA countries. Our choice of the P-ARDL model is due to its advantages over traditional co-integration estimating techniques. These include:

- 1. It can determine both long- and short-run dynamics as it can estimate both long-run and short-run parameters. (Hussain et al., 2017)
- 2. It accommodates either or both I(0) and I(1) series but not at I(2). (Asumadu-Sarkodie & Owusu, 2016; Ahmad & Du, 2017)
- 3. It allows different variables to be assigned different lag lengths and can estimate more than six variables. (Giles, 2013)
- 4. Its single-equation model set-up allows for easy analysis and interpretation. (Giles, 2013)

4. Data Analysis and Model Estimation

4.1. Data Tests

Firstly, we conduct stationary tests on our variables, followed by tests for cross-sectional dependence and then lag selection; then, we conduct a test for co-integration to confirm the appropriateness of the use of the P-ARDL model.

4.1.1. Panel ARDL Unit Root Test Result

We conduct stationary tests using the different robust unit root tests of Levin, Lin and Chu (LLC); Im, Pesaran and Shin (IPS) and the Augmented Dickey Fuller (ADF)-Fisher Chi-square. We engage the three tests to confirm the reliability of our results. The findings in Table 1 below reveal that all the variables become stationary after first difference (I(1)) as none of the series is stationary at level (I(0)) or after second difference (I(2)). Therefore, the unit root test result agrees with Pesaran et al. (2001) and thus, justifies our adoption of the P-ARDL model.

¹ See (Bildirici, 2014; Ahmad & Du, 2017).

Table 1. Levin, Lin & Chu; Im, Pesaran and Shin and ADF-Fisher Chi-square unit root tests

Variable	Levin, Lin	& Chu Uı	nit root test				
	(individual intercept)			and trend)			
	Order of	t*	P-Value	Order of	t*	P-Value	
	integration	Statistics		integration	Statistics		
Agricultural	I(1)	-18.6904	0.0000***	I(1)	-14.9001	0.0000***	
Value Added	,			,			
Labour	I(1)	-2.33856	0.0097***	I(1)	-1.84670	0.0324**	
Capital	I(1)	-4.97194	0.0000***	I(1)	-18.0400	0.0000***	
Degree of	I(1)	-21.0906	0.0000***	I(1)	-11.8305	0.0000***	
Openness	, ,			, ,			
Real	I(1)	-4.44740	0.0000***	I(1)	-2.33918	0.0097***	
Exchange rate	, ,			, ,			
GDP per	I(1)	-16.0746	0.0000***	I(1)	-11.2805	0.0000***	
capita	,			,			
Variable	Im, Pesaran	and Shin U	Init root test	Im, Pesaran	and Shin U	nit root test	
	(individual in			(individual in	tercept and tr	end)	
	Order of	t*	P-Value	Order of	t*	P-Value	
	integration	Statistics		integration	Statistics		
Agricultural	I(1)	-22.7067	0.0000***	I(1)	-19.3102	0.0000***	
Value Added	,			,			
Labour	I(1)	-5.91527	0.0000***	I(1)	-3.78677	0.0001***	
Capital	I(1)	-5.39121	0.0000***	I(1)	-18.7440	0.0000***	
Degree of	I(1)	-23.5289	0.0000***	I(1)	-17.9218	0.0000***	
Openness	, ,			, ,			
Real	I(1)	-9.34630	0.0000***	I(1)	-7.51436	0.0000***	
Exchange rate	,			,			
GDP per	I(1)	-17.1425	0.0000***	I(1)	-12.5304	0.0000***	
capita	, ,			, ,			
Variable	ADF-Fisher	Chi-square U	Jnit root test	ADF-Fisher Chi-square Unit root test			
	(individual in			(individual intercept and trend)			
	Order of	t*	P-Value	Order of	t*	P-Value	
	integration	Statistics		integration	Statistics		
Agricultural	I(1)	570.314	0.0000***	I(1)	434.041	0.0000***	
Value Added	,			,			
Labour	I(1)	179.421	0.0000***	I(1)	133.882	0.0000***	
Capital	I(1)	136.353	0.0000***	I(1)	426.480	0.0000***	
Degree of	I(1)	577.798	0.0000***	I(1)	415.563	0.0000***	
Openness							
Real	I(1)	288.378	0.0000***	I(1)	253.245	0.0000***	
Exchange rate							
GDP per	I(1)	414.772	0.0000***	I(1)	310.275	0.0000***	
capita		· · · -					
r	1	l	I.	1	1	1	

Source: Authors' computation using E-views 9.5 Statistical Package

"***" and "**" represent 1% and 5% significance level, respectively

4.1.2. Residual Cross-Sectional Dependence Tests

The cross-section is normally removed during computation of correlations to mitigate cross-sectional dependency. (Pesaran, 2007) Here, we run the test to confirm that there is no presence of cross-sectional dependence and further justify the use of the panel data model in SSA. In this regard, the robust Breusch-Pagan LM, Pesaran scaled LM and Pesaran Cross Dependence (CD) tests are engaged to confirm if the residuals are correlated or not. The hypotheses for the cross-sectional dependence are:

Null Hypothesis: H_0 : $\theta = 1$ - cross-sectional dependence does not exist among the variables.

Alternative Hypothesis: H_1 : $\theta \neq 1$ - cross-sectional dependence exists among the variables.

The guideline is that the null hypothesis is accepted and the alternative hypothesis is rejected when the P-value is below 5% while the alternative hypothesis is accepted and the null hypothesis is rejected when the P-value exceeds 5%.

Table 2. Cross-Sectional Dependence Test Result Summary

Test	Statistic	d.f.	Prob.	
Breusch-Pagan LM	843.2241	666	0.0000***	
Pesaran scaled LM	4.609311		0.0000***	
Pesaran CD	7.174337		0.0000***	

Source: Authors' computation using E-views 9.5 Statistical Package

As shown in Table 2 above, the P-values of the Breusch-Pagan LM, Pesaran scaled LM and Pesaran CD are all significant at 1% level (P < 1%); hence we accept the null hypothesis that there is no cross-sectional dependence among the variables in the model while the alternative hypothesis that there is cross-sectional dependence (correlation) among the residuals (error term) is rejected.

4.1.3. Optimal Lag Selection

The optimal number of variable lags to be selected is determined by the robust Akaike Information Criterion (AIC), Schwarz Information Criterion (SIC) and Hannan-Quinn information criterion (HQ). The procedure is to select the model with the lowest value of AIC as this is the best model. We therefore select the lowest AIC value as the optimal lag for our analysis. (Lutkepohl, 2006) Of the nine estimated models, our findings specify the most appropriate model with ARDL (3, 3, 3, 3, 3), as depicted in Table 3 below.

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[&]quot;***" represents 1% significance level.

¹ See (Bahmani-Oskooee & Brooks, 2003; Ahmad & Du, 2017).

Table 3. Optimal Lag Selection

Model	LogL	AIC*	SIC	HQ	Specification
9	1780.872264	-2.521439	1.427397	-1.008913	ARDL(3, 3, 3, 3, 3, 3)
6	1624.068873	-2.239880	1.502591	-0.806399	ARDL(2, 3, 3, 3, 3, 3)
3	1501.156170	-2.037970	1.498135	-0.683533	ARDL(1, 3, 3, 3, 3, 3)
8	1329.647796	-1.895765	1.021243	-0.778461	ARDL(3, 2, 2, 2, 2, 2)
5	1277.802473	-1.860875	0.849767	-0.822616	ARDL(2, 2, 2, 2, 2, 2)
2	1229.180432	-1.833562	0.670715	-0.874347	ARDL(1, 2, 2, 2, 2, 2)
7	1117.118162	-1.831065	0.054114	-1.108984	ARDL(3, 1, 1, 1, 1, 1)
4	1074.669680	-1.818260	-0.139447	-1.175223	ARDL(2, 1, 1, 1, 1, 1)
1	1033.254683	-1.807884	-0.335437	-1.243891	ARDL(1, 1, 1, 1, 1, 1)

Source: Authors' computation using E-views 9.5 Statistical Package

LR: sequential modified LR test statistic (each test at 5% level)

4.1.4. Measuring the Strength of the Selected Model

The graph in figure 3 below verifies the regression model selection of the AIC rather than the FPE, SIC and HQ criteria as revealed in table 3 above. The AIC criteria graph illustrates the top nine different P-ARDL models in order to select the most appropriate model which has the least AIC value. The first ARDL (3, 3, 3, 3, 3, 3) model fulfills the criteria of the most appropriate model compared to the other criteria as it reveals the least value of the AIC at -2.521 This is followed by the second most appropriate ARDL (2, 3, 3, 3, 3, 3) model with the value of -2.239.

^{*}depicts lag order selected by the criterion

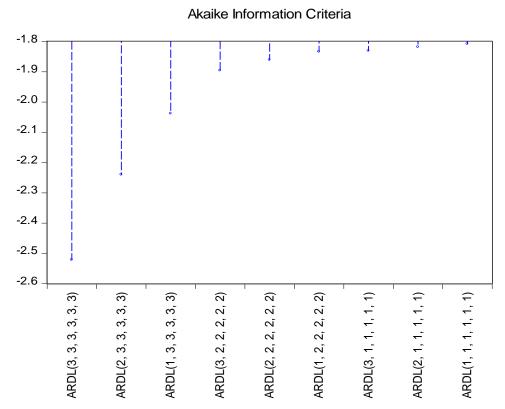


Figure 2. Summary of the Strength of the Model Selection

Source: Authors' computation using E-views 9.5 Statistical Package

4.2. Interpretation of Regression Results

4.2.1. The Panel ARDL Regression Model

As shown in Table 4 below, the P-ARDL model analysis reveals that all the variables are statistically significant in influencing agricultural output in the long run (P(0.0000) < 1%). The table also shows that labour (LABR) and the real exchange rate (REXC) have a positive long-run significant impact on agricultural production in SSA. This confirms the findings of previous empirical studies that an increase (decrease) in the two factors would result in a corresponding increase (decrease) in agricultural production. However, this analysis disagrees with Muraya and Ruigu (2017) that posited that the exchange rate has a negative relationship with agricultural output, although our result agrees with their opinion that labour exerts a positive impact on agricultural production. The result is also inconsistent with Bashir

¹ See (Abugamea, 2008; Yu & Nin-Pratt, 2011; Brownson et al., 2012; Enu & Attah-Obeng, 2013; Hart et al., 2015; Wagle, 2017).

(2015) and Enu and Attah-Obeng's (2013) view that labour has an inverse relationship with agricultural production even though they agree that the real exchange rate has a positive association with agriculture output.

The study found that other variables such as capital (CAPI), degree of openness (DOPEN) and income per capita (GDPPC) have a significant negative relationship with agricultural output in SSA. This concurs with the findings of some previous studies¹ that an increase (decrease) in the factors would result in a corresponding decrease (increase) in agricultural production. However, this result is contrary to the findings of Alene (2010), Hart et al., (2015) and Sheng et al. (2017) that concluded that trade, the degree of openness and capital have a positive relationship with agricultural production.

None of the independent factors is statistically significant in impacting agricultural production in the short run in SSA except the second-year lagged value of capital (CAPI(-2)), which is significant at 5% level (P (0.0223) < 5%), consistent with Chisasa and Makina (2015). This implies that the Cobb-Douglass production function model does not support short-run estimation of agricultural production in SSA during the reviewed period. Hence, the estimated panel ARDL model for our study reveals a long run, dynamic significant effect on agricultural production in SSA, providing evidence of a cointegrating dynamic impact in boosting agricultural productivity in the region. The cointegrating factor (COINTEQO1) further validates the appropriateness of the model whose coefficient must be negative and statistically significant as confirmed in Table 4 below at -0.937215 and (P (0.0000) < 1%), respectively. Further confirmation of the presence of co-integration among the variables can be obtained using the Error Correction Mechanism (ECM). The guideline is that the Error Correction Term (ECT) must be negative and significant to denote co-integration among the variables. (Engle & Granger, 1987)

As expected, the results in table 4 below show that a 1% rise in labour (LABR) raises agricultural output (AGVA) by 280% in the long run in SSA. The positive relationship is due to increased labour productivity and the growing rural population in the region as most large and small households in SSA countries use available arable land for agricultural production. This view is supported by Yu and Nin-Pratt (2011). The positive association between labour and the agricultural sector is also due to the fact that this sector employs almost 80% of the total labour force in the region. Surprisingly, a 1% increase in capital (CAPI) leads to an almost 8% reduction in agricultural productivity in the long run and 43.6% in the short run in SSA. This negative relationship corroborates the Diminishing Marginal Productivity theory (DMPT). Due to capital stock accumulation in most SSA economies, it has gradually been substituting for the labour factor in the agricultural production process. Its

¹ See (Abugamea, 2008; Brownson et al., 2012; Enu & Attah-Obeng, 2013; Bashir, 2015; Akande et al., 2017; Almasifard & Khorasani, 2017).

excessive utilization beyond the optimal point in the long run results in diminishing agricultural returns. The P-ARDL model short-run estimate confirms the DMPT, as the second-year lagged value of capital (CAPI(-2) of 0.0223 shows a positive significant relationship with agricultural output in the short run compared to a negative significant relationship in the long run in SSA. This is consistent with Bashir (2015) and Wagle's (2017) findings. Contrary to our expectations, table 4 below shows that, a 1% increase in the real exchange rate (REXC) leads to a 7.7% rise in agricultural output in SSA in the period under review. According to economic theory, currency appreciation or a rise in the real exchange rate (REXC) leads to a trade deficit, discouraging exports and encouraging imports. Hence, the declining level of exports discourages domestic agricultural production while increased imports increase foreign competition with local producers and increase production costs, leading to low productivity¹ Similarly, a depreciating currency or real exchange rate reduction against a strengthening US dollar discourages imports, encourages exports and boosts agricultural production as international competition is reduced. However, the model estimation in our study could be attributed to the fact that the monetary authorities' efforts to formulate policies to stabilize the longrun exchange rate in most SSA countries are beginning to produce results. This view is shared by Enu and Attah-Obeng (2013). An increase of 1% in the degree to which the SSA economy is open to trade (DOPEN) reduces agricultural productivity by 14.7% in the long run. This is because a major share of the exports of most SSA countries consists of non-agricultural resources such as oil and other natural resources, resulting in the resource-curse effect. (Brownson et al., 2012) This implies that SSA countries engaged in increased export of non-agricultural goods are abandoning their agricultural sector. Most are dependent on imported agricultural goods such as rice and other cereals to supplement waning domestic production, especially those experiencing drought and political /economic crisis. A rise of 1% in income per capita (GDPPC) results in decline in agricultural output of 50.6% in SSA. This is indicative of the low return on investment that characterizes the sector in this region, making it an unattractive investment option. Rather than boosting production, agricultural producers with surplus income are likely to invest in other more return-friendly sectors. This trend is fueled by poor land tenure systems, poor irrigation and technology, the high cost of seed and storage facilities, high production costs, and poor marketing of agricultural produce and lack of access to credit facilities. This line of thought concurs with Enu and Attah-Obeng's (2013) observations.

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¹ See (Kutu & Ngalawa, 2016).

Table 4. Panel ARDL Model Estimated Result

		Dependent Varia				
		Method:				
		Sample: 1990		-		
	Mo	del selection method: Ak	aike info criterion (AI)	C)		
	Dynamic reg	ressors (3 lags, automatic): LABR CAPI REXC	DOPEN GDPPC		
		Selected Model: AR	DL (3, 3, 3, 3, 3, 3)			
Variable	С	oefficient	Std. Error		t-Statistic	Prob.*
			n Equation			
LABR		.791415	0.264684		10.54623	0.0000***
CAPI		0.079338	0.015326		-5.176761	0.0000***
REXC		.077318	0.011123		6.951167	0.0000***
DOPEN		0.147267	0.018988		-7.755892	0.0000***
GDPPC	-	0.506977	0.035132		-14.43058	0.0000***
			n Equation			
COINTEQ01	-0.937215	0.225315	-4.159580	0.0000***		
D(AGVA(-1))	0.088678	0.184910	0.479576	0.6319		
D(AGVA(-2))	-0.236445	0.213581	-1.107050	0.2693		
D(LABR)	-9.056181	10.29492	-0.879674	0.3799		
D(LABR(-1))	6.897724	11.86685	0.581260	0.5616		
D(LABR(-2))	7.546452	8.928223	0.845236	0.3988		
D(CAPI)	-0.436989	0.364921	-1.197490	0.2322		
D(CAPI(-1))	-0.553212	0.440287	-1.256482	0.2101		
D(CAPI(-2))	0.678344	0.294948	2.299877	0.0223**		
D(REXC)	-0.122024	0.080770	-1.510764	0.1321		
D(REXC(-1))	0.327910	0.480407	0.682568	0.4955		
D(REXC(-2))	0.079321	0.111131	0.713758	0.4760		
D(DOPEN)	0.031504	0.128965	0.244280	0.8072		
D(DOPEN(-1))	0.195715	0.135883	1.440326	0.1510		
D(DOPEN(-2))	-0.009797	0.149298	-0.065622	0.9477		
D(GDPPC)	0.206829	0.379186	0.545455	0.5859		
D(GDPPC(-1))	0.521395	0.397418	1.311954	0.1907		
D(GDPPC(-2))	0.733130	0.458409	1.599294	0.1110		
C	0.012682	0.006995	1.813079	0.0710*		

Source: Authors' computation using E-views 9.5 Statistical Package

"***", "**" and "*" represent 1%, 5% and 10% significance level, respectively

4.3. Panel-ARDL Co-integration Result

The existence of co-integration among the variables is determined using the Wald Test. As shown in table 5 below, the P-value is 0.0000. This illustrates that the variables are statistically significant at 1% significance level. The hypotheses for the Wald co-integration test are given below:

Null Hypothesis: H_0 : C(1)=C(2)=C(3)=C(4)=C(5)=0: There is no cointegration among the variables

Alternative Hypothesis: H_1 : $C(1)=C(2)=C(3)=C(4)=C(5)\neq 0$: There is cointegration among the variables

Given that P < 1%, the null hypothesis of no evidence of co-integration is rejected and the alternative hypothesis is accepted, corroborating our earlier model estimation of co-integration among labour, capital, the real exchange rate, degree of openness and per-capita income in impacting agricultural production in SSA. The F-statistical value indicates evidence of co-integration or not among the variables by comparing it to the Pesaran critical upper bound value at 5% level of significance at Unrestricted trend and No Intercept. The guideline is that if the F-value exceeds the upper bound critical value at 5% significance level, we reject the null hypothesis of no co-

integration and accept the alternative hypothesis, thus indicating that all the variables move together in the long run. As seen in table 5 below, the F-statistical value at 81.32128 exceeds the upper bound of the Pesaran critical value of 4.85 at 5% level. (Pesaran et al., 2001) The F-statistical value is both positive and significant, substantiating the evidence that agricultural production, labour, capital, the real exchange rate, the degree of openness and per-capita income move together in the long run using the P-ARDL model.

Table 5. Panel-ARDL Co-integration Result

Wald Test				
Equ	uation: P-ARDL			
Test Statistic	Value	Df	Probability	
F-statistic	81.32128	(5, 254)	0.0000***	
Chi-square	406.6064	5	0.0000***	

Source: Authors' computation using E-views 9.5 Statistical Package

4.3.1. Panel-ARDL Error Correction Model (ECM)

The ECM is engaged to achieve the core objective of this study, which is to examine the long- and short-run dynamics of the P-ARDL model. The ECT coefficient determines the speed at which the variables move back to equilibrium, which is the speed of adjustment. An appropriate ECM is indicated by a value which is less than 1, has a negative coefficient and is statistically significant. As depicted in Table 6 below, the ECT fulfills the conditions of a good model highlighted earlier, as its value of -0.292124 is less than 1; the negative coefficient signals the presence of disequilibrium in the previous short-run period of the P-ARDL system and the speed of adjustment from the short-run divergence towards long-run equilibrium is at the relatively low rate of 29.2% per year of agricultural production's contribution to GDP in SSA. This implies that an approximate 29% divergence from long-run equilibrium in the short-run period of the factors that influence agricultural production in SSA is corrected annually. Furthermore, the statistically significant value of the ECT at 5% level signifies that the factors affecting agricultural production in SSA can co-move to a long-run equilibrium. This is consistent with Boutabba (2014) and Sebri and Ben-Salha's (2014) studies that found evidence of a stable, long-run relationship illustrated by, a statistically significant and negative ECT.

Table 6. Error Correction Term

Variable	Coefficient	Std. Error	t-Statistic	Prob.
ECT(-1)	-0.292124	0.128096	-2.280516	0.0228**

Source: Authors' computation using E-views 9.5 Statistical Package.

[&]quot;***" represents 1% significance level

"**" represents 5% significance level

4.4. Short-Run Causality Tests

The short-run causality estimates seek to determine whether there is a joint causal relationship running from the independent variables to the dependent variable. Employing the Wald test, we test if the two lagged periods of each explanatory factor jointly affect agricultural productivity in the short-run in SSA. The hypotheses are given below:

Null Hypothesis: H_0 : There is no short run causality between lagged independent variables and the dependent variable

Alternative Hypothesis: H_1 : There is short run causality between lagged independent variables and the dependent variable

As depicted in Table 7 below, we test whether the two lagged periods of labour (LABR(-1) and LABR(-2)) jointly affect agricultural productivity in SSA in equation 1; equation 2 determines whether the two lagged periods of capital (CAPI(-1) and CAPI(-2)) jointly affect agricultural productivity in SSA; equation 3 tests whether the two lagged periods of real exchange rate (REXC(-1) and REXC(-2)) jointly influence agricultural productivity; equation 4 determines whether the two lagged periods of degree of openness (DOPEN(-1) and DOPEN(-2)) explain agricultural productivity; and equation 5 determines whether the two lagged periods of income per capita (GDPPC(-1) and GDPPC(-2)) jointly influence agricultural productivity. The results show that none of the variables is statistically significant in the short-run period except degree of openness which is significant with a value of 0.0403 at 5% level. Hence, we accept the null hypothesis (H_0) in the cases of LABR(-1) and LABR (-2), CAPI(-1) and CAPI (-2), REXC(-1) and REXC(-2) and GDPPC(-1) and GDPPC (-2) that there is no joint short-run causality running from the two lagged periods of the explanatory variables to agricultural productivity in SSA. However, the two lagged periods of degree of openness (DOPEN(-1) and DOPEN(-2)) jointly have a significant influence on agricultural production in the short run in SSA.

Table 7. Short-Run Causality Test

	Wald Test		
	Equation 1: P-ARDL. H_0 : C(4)=C(5)=0		
Test Statistic	Value	Df	Probability
F-statistic	1.145041	(2, 800)	0.3187
	Equation 2: P-ARDL. <i>H</i> ₀ : C(6)=C(7)=0		•
F-statistic	1.268800	(2,800)	0.2817
	Equation 3: P-ARDL. H_0 : C(8)=C(9)=0		
F-statistic	0.681717	(2,800)	0.5060
	Equation 4: P-ARDL. H_0 : C(10)=C(11)=0		
F-statistic	3.224321	(2,800)	0.0403**
	Equation 5: P-ARDL. H_0 : C(12)=C(13)=0	•	
F-statistic	1.113108	(2,800)	0.3290

Source: Authors' computation using E-views 9.5 Statistical Package

5. Conclusion and Policy Recommendations

This study empirically investigated the long- and short-run dynamics of agricultural productivity in SSA from 1990 to 2016 employing the Panel ARDL modelling technique. The results show the presence of co-integration among the dependent variable, which is agricultural production, and the explanatory variables. Similar findings have been reported by single country case studies. (Yu & Nin-Pratt, 2011; Brownson et al., 2012; Enu & Attah-Obeng, 2013; Bashir, 2015; Wagle, 2017) The model estimate depicts that only the explanatory factors of labour (LABR) and the real exchange rate (REXC) affect agricultural productivity significantly and positively in the long run in SSA. Other factors considered such as capital (CAPI), degree of openness (DOPEN) and per-capita income (GDPPC) had a negative but significant relationship with agricultural output. (Abugamea, 2008; Akande et al., 2017; Almasifard & Khorasani, 2017) In contrast, all the variables, except the second-year lagged capital value (CAPI(-2)), were not found to significantly determine agricultural productivity in the short run in SSA. It is thus concluded that the P-ARDL Cobb-Douglas production function model does not hold in the short run but in the long run. In line with general economic theory, the model shows that a 1 unit increase in labour (LABR) increases agricultural output (AGVA) by 280% in the long run in SSA; however, contrary to a priori expectation, a 1% increase in capital (CAPI) leads to an 8% and 43.6% reduction in agricultural productivity in the long run and short run, respectively, in the region in line with the diminishing marginal productivity theory (DMPT). Contrary to our expectation, a 1% increase in the real exchange rate (REXC) leads to a 7.7% rise in agricultural productivity in

[&]quot;**" represents 5% significance level

SSA in the period under review. Consistent with standard economic theory, an increase of 1% in the degree of openness of the SSA economy (DOPEN) reduces agricultural productivity by 14.7% in the long run. Likewise, a 1% rise in income per capita (GDPPC) results in a decline of 50.6% in agricultural output in SSA.

In summary, the five independent indicators examined in the study significantly impact agricultural productivity in the long run but not in the short run except the second-year lagged value of gross capital formation (CAPI(-2)). Furthermore, the Wald test revealed that only the first-year and second-year lagged values of degree of openness (DOPEN(-1) and DOPEN(-2)) jointly and significantly explain agricultural productivity in the short run in SSA. The empirical findings reveal a comovement relationship among the variables from short-run dis-equilibrium to long-run equilibrium of agricultural productivity in SSA as shown by the significant ECT value and adjustment speed of 29.2%. It can thus be concluded that the influence of the explanatory variables enhances agricultural output in the long run and that there is a possibility of achieving long-run equilibrium among agricultural productivity, labour, capital, the real exchange rate, degree of openness and income per capita in SSA

In view of these findings, agricultural policies should aim to attract and retain both existing and potential producers and deliver significant returns to investors, thus boosting production, increasing agriculture's contribution to GDP growth and stimulating economic growth in SSA. The capital-labour ratio should be put to optimal and efficient use with a view to maximizing agricultural output in the region. An effective mix and implementation of fiscal and monetary policies is also essential to maintain inflation at the lowest possible rate and stabilize the exchange rate in the short- and long-run in order to develop this sector. The monetary authorities should ensure exchange rate stability in order to promote exports and discourage imports, hence boosting local production. The fiscal authorities should create a conducive environment by formulating policies that improve the land tenure system, provide irrigation facilities and affordable technology, promote ease of access to seeds and storage facilities, implement government-assisted marketing of agricultural produce and offer easy access to credit facilities provided by the financial sector. This would significantly reduce production costs and enhance agricultural productivity in SSA.

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6. Bibliography

Abugamea, G.H. (2008). A Dynamic Analysis for Agricultural Production Determinants in Palestine: 1980-2003. In Proceedings of *International Conference on Applied Economics, ICOAE*, pp. 3-10.

Ajao, A.O. (2011). Empirical analysis of agricultural productivity growth in Sub-Saharan Africa: 1961–2003. Libyan Agricultural Resource Center Journal International, 2(5), pp. 224-231.

Akpan, S.B.; Udoh, E.J. & Patrick, I.V. (2015). Assessment of economic policy variables that modeled agricultural intensification in Nigeria. *Russian Journal of Agricultural and Socio-Economic Sciences*, 41(5).

Ahmad, N. & Du, L. (2017). Effects of energy production and CO2 emissions on economic growth in Iran: ARDL approach. *Energy Volume*, 123, 15 March 2017, pp. 521-537.

Akande, O.R.; Obekpa, H.O. & Fani D.R. (2017). Improving Agricultural Productivity Growth in Sub-Saharan Africa. In: Heshmati A. (eds) Studies on Economic Development and Growth in Selected African Countries. *Frontiers in African Business Research*. *Springer*, Singapore.

Alene, A.D. (2010). Productivity growth and the effects of R&D in African agriculture. *Agricultural Economics*, 41(3-4), pp. 223-238.

Almasifard, M. & Khorasani, S.T. (2017). Relationship between Domestic Production in Agricultural and Industrial Sectors and Purchasing Power by Controlling for International Trade Variables (Iran). *International Journal of Economics and Financial Issues*, 7(4), pp. 244-253.

Alvarez-Cuadrado, F.; Van Long, N. & Poschke, M. (2017). Capital–labor substitution, structural change, and growth. *Theoretical Economics*, 12(3), pp. 1229-1266.

Asumadu-Sarkodie, S. & Owusu, P.A. (2016). The relationship between carbon dioxide and agriculture in Ghana: A comparison of VECM and ARDL model. *Environmental Science and Pollution Research*, 23(11), pp. 10968-10982.

Awan, A.G. & Yaseen, G. (2017). Global Climate Change and its Impact on Agriculture Sector in Pakistan. *American Journal of Trade and Policy*, 4(1), pp. 41-48.

Bahmani-Oskooee, M. & Brooks, T.J. (2003). A new criteria for selecting the optimum lags in Johansen's cointegration technique. *Applied Economics*, 35(8), pp. 875-880.

Barrett, C.B.; Christiaensen, L.; Sheahan, M. & Shimeles, A. (2017). On the structural transformation of rural Africa. *Journal of African Economies*, pp. 1-25.

Bashir, F. (2015). Energy Consumption and Agriculture Sector in Middle Income Developing Countries: A Panel Data Analysis. *Pakistan Journal of Social Sciences (PJSS)*, 35(1).

Bildirici, M.E. (2014). Relationship between biomass energy and economic growth in transition countries: panel ARDL approach. *Gcb Bioenergy*, 6(6), pp. 717-726.

Block, S.A. (1995). The recovery of agricultural productivity in sub-Saharan Africa. *Food Policy*, 20(5), pp. 385-405.

Bond, M.E. (1983). Agricultural responses to prices in Sub-Saharan African countries. *IMF Staff Papers*, 30(4), pp. 703-726.

Boutabba, M.A. (2014). The impact of financial development, income, energy and trade on carbon emissions: evidence from the Indian economy. *Economic Modelling*, 40, pp. 33-41.

Brownson, S.; Vincent, I.M.; Emmanuel, G. & Etim, D. (2012). Agricultural productivity and macro-economic variable fluctuation in Nigeria. *International Journal of Economics and Finance*, 4(8), p. 114.

Chisasa, J. & Makina, D. (2015). Bank credit and agricultural output in South Africa: Cointegration, Short run Dynamics and Causality. *Journal of Applied Business Research*, 31(2), pp. 489-500.

Christiaensen, L.; Demery, L. & Kuhl, J. (2011). The (evolving) role of agriculture in poverty reduction - An empirical perspective. *Journal of Development Economics*, 96(2), pp. 239-254.

Chudik, A. & Pesaran, M. H. (2013). Large Panel Data Models with Cross-Sectional Dependence: A Survey. Center for Applied Financial Economics (CAFE) research paper no. 13.15. In B.H. Baltagi (Ed.), forthcoming in *The Oxford Handbook on Panel Data*. Oxford University Press.

Collier, P. & Dercon, S. (2014). African Agriculture in 50 Years: Smallholders in a Rapidly Changing World? *World Development*, 63, pp. 92-101.

Conceição, P.; Levine, S.; Lipton, M. & Warren-Rodríguez, A. (2016). Toward a food secure future: Ensuring food security for sustainable human development in Sub-Saharan Africa. *Food Policy*, 60, pp. 1-9

De Vries, G.; Timmer, M. & De Vries, K. (2015). Structural transformation in Africa: Static gains, dynamic losses. *The Journal of Development Studies*, 51(6), pp. 674-688.

Diao, X.; Hazell, P. & Thurlow, J. (2010). The role of agriculture in African development. *World Development*, 38(10), pp. 1375-1383.

Engle, Robert F. & Granger, W.J. (1987) Co-integration and Error Correction: Representation, Estimation, and Testing. *Econometrica: Journal of the Econometric Society*, pp. 251-276.

Enu, P. & Attah-Obeng, P. (2013). Which macro factors influence agricultural production in Ghana? *Academic Research International*, 4(5), pp. 333-346.

Faridi, M.Z. & Murtaza, G. (2014). Disaggregate energy consumption, agricultural output and economic growth in Pakistan. *The Pakistan Development Review* 52:4 Part I, Winter 2013, pp. 493–516.

Fuglie, K. & Rada, N. (2013). Resources, policies, and agricultural productivity in sub-Saharan Africa. *Economic Research Report*, 145, USDA Economic Research Service, Washington, DC.

Feenstra, R.C.; Inklaar, R. & Timmer, M.P. (2015). The next generation of the Penn World Table. *The American Economic Review*, 105(10), pp. 3150-3182.

Fulginiti, L.E.; Perrin, R.K. & Yu, B. (2004). Institutions and agricultural productivity in Sub-Saharan Africa. *Agricultural Economics*, 31(2-3), pp. 169-180.

Garrity, D.P.; Akinnifesi, F.K.; Ajayi, O.C.; Weldesemayat, S.G.; Mowo, J.G.; Kalinganire, A.; Larwanou, M. & Bayala, J. (2010). Evergreen Agriculture: a robust approach to sustainable food security in Africa. *Food security*, 2(3), pp. 197-214.

Giles, D. (2013). Econometrics beat: Dave Giles' blog: ARDL models - Parts I and 2.

Hart, J.; Miljkovic, D. & Shaik, S. (2015). The impact of trade openness on technical efficiency in the agricultural sector of the European Union. *Applied Economics*, 47(12), pp. 1230-1247.

Hilson, G. & McQuilken, J. (2014). Four decades of support for artisanal and small-scale mining in sub-Saharan Africa: A critical review. *The Extractive Industries and Society*, 1(1), pp. 104-118.

Hussain, I.; Khan, Z.; Khan, M.I.; Khalid, S.; Kiran, A. & Hussain, T. (2017). Long Run and Short Run Relationship among Gross Domestic Saving, Net Bilateral Foreign Aid, External Debt and Economic Growth in Pakistan. *Dynamics of Economics*, 1(1), pp. 1-7.

Imahe, O.J. & Alabi, R.A. (2005). The determinants of agricultural productivity in Nigeria. *Journal of Food, Agriculture and Environment*, Vol. 3, no. 2, pp. 269-274.

International Monetary Fund. (2017). World Economic Outlook. Africa, Sub-Saharan. Restarting the Growth Engine. Washington, DC. Jan.

Jayne, T.S. & Rashid, S. (2013). Input subsidy programs in sub-Saharan Africa: a synthesis of recent evidence. *Agricultural Economics*, 44(6), pp. 547-562.

Jedwab, R. & Vollrath, D. (2015). Urbanization without growth in historical perspective. *Explorations in Economic History*, 58, pp. 1-21.

Kahsay, G.A. & Hansen, L.G. (2016). The effect of climate change and adaptation policy on agricultural production in Eastern Africa. *Ecological Economics*, 121, pp. 54-64.

Kamlongera, P.J. & Hilson, G. (2011). Poverty alleviation in rural Malawi: is there a role for artisanal mining? *Journal of Eastern African Studies*, 5(1), pp. 42-69.

Kutu, A.A. & Ngalawa, H. (2016). Dynamics of Industrial Production in Brics Countries. *International Journal of Economics and Finance Studies*, Vol 8, No 1, pp. 1-25.

Lewis, W.A. (1954). Economic development with unlimited supplies of labour. *The Manchester School*, 22(2), pp. 139-191.

Lusigi, A. & Thirtle, C. (1997). Total factor productivity and the effects of R&D in African agriculture. *Journal of International Development*, 9(4), pp. 529-538.

Lutkepohl, H. (2006). Structural Vector Autoregressive Analysis for Cointegrated Variables. *Adv Econometric Analysis*, 90 (2006), pp. 75-88.

Mosley, P. & Smith, L. (1989). Structural adjustment and agricultural performance in Sub-Saharan Africa 1980–87. *Journal of International Development*, 1(3), pp. 321-355.

Muraya, B.W. & Ruigu, G. (2017). Determinants of Agricultural Productivity in Kenya, *International Journal of Economics, Commerce and Management*, Vol. V, Issue 4, April 2017.

Nin Pratt, A. & Yu, B. (2008). An updated look at the recovery of agricultural productivity in Sub-Saharan Africa. *International Food Policy Research Institute Discussion Paper*, p. 787.

Owuor, J. (1999). Determinants of Agricultural productivity in Kenya, Paper presented at the Conference on Strategies for Raising Productivity in Agriculture, Egerton University/Tegemeo Institute of Agricultural Policy and Development, Nairobi Kenya.

Pesaran, M.H. & Shin, Y. (1998). An Auto-Regressive Distributed Lag modelling approach to cointegration analysis. *Econometric Society Monographs*, 31, pp. 371-413.

Pesaran, M.H.; Shin, Y. & Smith, R.J. (2001). Bounds testing approaches to the analysis of level relationships. *Journal of Applied Econometrics*, 16(3), pp. 289-326.

Pesaran, H.M. (2007). A simple panel unit root test in the presence of cross-section dependence. *Journal of Applied Econometrics*, 22, no. 2, pp. 265-312.

Rafindadi, A. & Zarinah, Y. (2013). An Application of Panel ARDL in Analysing the Dynamics of Financial Development and Economic Growth in 38 Sub-Saharan African Continents. In Proceedings - Kuala Lumpur International Business, Economics and Law Conference.

Sebri, M. & Ben-Salha, O. (2014). On the causal dynamics between economic growth, renewable energy consumption, CO 2 emissions and trade openness: fresh evidence from BRICS countries. *Renewable and Sustainable Energy Reviews*, 39, pp. 14-23.

Sheng, Y.; Jackson, T.; Zhao, S. & Zhang, D. (2017). Measuring Output, Input and Total Factor Productivity in Australian Agriculture: An Industry-Level Analysis. *Review of Income and Wealth*, 63(s1).

Smith, L.D. (1989). Structural adjustment, price reform and agricultural performance in sub-Saharan Africa. *Journal of Agricultural Economics*, 40(1), pp. 21-31.

Ssozi, J.; Asongu, S.A. & Amavilah, V.H.S. (2017). Is Aid for Agriculture Effective in Sub-Saharan Africa? *African Governance and Development Institute WP/17/035*. Available at SSRN: https://ssrn.com/abstract=3034132.

Wagle, T.P.S. (2017). Spatial Analysis of Cobb-Douglas Production Function in Agriculture Sector of Nepal: An Empirical Analysis. *Journal of Advanced Academic Research*, 3(2), pp. 101-114.

World Bank (2007). World Development Report 2008: Agriculture for Development. Washington, DC. World Bank. https://openknowledge.worldbank.org/handle/10986/5990.

Yu, B. & Nin-Pratt, A. (2011). Agricultural Productivity and Policies in Sub-Saharan Africa. *IFPRI Discussion Paper*, 01150. Washington, DC: International Food Policy Research Institute.

Yuan, Z. (2011). Analysis of agricultural input-output based on Cobb-Douglas production function in Hebei Province, North China. *African Journal of Microbiology Research*, 5(32), pp. 5916-5922.