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Original Research Article

Drivers of agricultural productivity: Evidence from transforming economies

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Abstract

This study empirically investigates the drivers of agricultural productivity in transforming economy. The study used a 35-year period (1980–2014) panel data sourced from World Development Indicators, Penn World Table, United States Department of Agriculture and Statistics on Public Expenditure for Economic Development. Data used for the study include Agricultural Productivity (AP), Real Gross Domestic Product (GDP), Government Agricultural Expenditure (EXP), Agricultural Trade Barrier (ATB), Consumer Price Index (CPI), Farm Machinery (MACH), Fertiliser (FERT), Human Capital (HCAP) and Irrigation (IRRG). Data were analysed using Impulse Response Function, Levin-Lin-Chu unit root test, Johansen-Fisher Panel Cointegration test and Panel Least Squares regression technique. Impulse Response Function revealed that l_n (GDP)reacted negatively to a shock from l_n (Agricultural Productivity). Levin-Lin-Chu unit root test revealed that the variables were stationary either at level or at first difference. The result of the Johansen-Fisher panel cointegration test showed that for every case at 5 percent level of significance, we reject null hypothesis of no cointegration. Panel Least Squares revealed that Agricultural Trade Barrier ($\alpha = 0.0531, p < 0.05$), Human Capital ($\alpha = 1.2409, p < 0.01$) and Irrigation ($\alpha = 0.0771, p < 0.01$) increased Agricultural Productivity. However, Fertilizer ($\alpha = -0.0730, p < 0.01$) decreased Agricultural Productivity. This study therefore concluded that Agricultural Productivity will grow in transforming economy with trade restriction on imported agricultural tradable commodities, increased investment in human capital and expansion in irrigation application. The study therefore recommends measures that will protect domestic agriculture, capacity building of the farmers and improved irrigation infrastructure that will enhance small scale farmers for all-season cropping.

Keywords: Agricultural growth determinants; developing countries; food security; impulse response function; panel least square; total factor productivity

INTRODUCTION

Agricultural Productivity measures the efficiency with which inputs were transformed into outputs in a given economy (Shittu and Odine, 2014). Osinowo and Sanusi (2018) noted that there is no greater engine for driving growth, reducing poverty and hunger than investing in agriculture, especially in agriculture-based and transforming economies. Thus, agricultural development becomes an important pre-condition of structural transformation towards industrial development, as it precedes and promotes industrialization.

Under the circumstances whereby agricultural growth is accounted for mostly by land expansion, which is not sustainable in the long run, agricultural productivity can be employed to enhance longer-term sustainability in the nexus of population growth rate and land scarcity. Frisvold and Lomax (1991) noted that the gap in agricultural productivity between the richest and poorest nations continues to grow, and many poorer nations face higher food prices and insecure supplies of food. Therefore, enhancing and accelerating sustainable agricultural productivity is a central component of a comprehensive strategy to meet the rising demands of food.

The World Bank (2008) in the The World Development Report (2008) classifies countries according to contribution of agriculture to economic growth and the share of the poor in the rural sector. In "agriculture-based" countries, agriculture contributes 20% or more to Gross Domestic Product (GDP) and more than half of the poor live in rural areas. In "transforming" economies, agriculture contributes less than 20% but poverty is still mostly rural, while in "urbanised" economies, agriculture contributes less than 7% to GDP and poverty is mostly urban.

World Development Report (2008) further argues that growth in the agricultural sector contributes proportionately more to poverty reduction than growth in any other economic sector and therefore, the focus should be on the agricultural sector when aspiring to reach Millennium Development Goals. However, while the agricultural sector may have in recent years contributed significantly to improved growth performance in many transforming economies, its actual contribution appears to be much short of overall potential. The quality of agricultural growth remains questionable considering the ample evidences of low productivity, poor economic competitiveness and weak linkages to other sectors.

Agricultural productivity has come to be understood as a powerful driver of growth that raises people out of poverty and contributes to overall development (Christiaensen et al., 2017). As reported by Ligon and Sadoulet (2018), agricultural productivity growth is widely considered as the most effective means of addressing rural poverty and a key pathway out of poverty. Growth in agriculture reduces poverty more than growth elsewhere in an economy. Ivanic and Martin (2018) noted that one percent increase in agricultural gross domestic product (GDP) per worker yields roughly double the impact on extreme poverty and concluded that raising agricultural productivity helps to lower food prices and increase real rural and urban wage.

Several empirical studies such as Nkamleu (2007), Benin et al. (2008), Shittu and Odine (2014), Ligon and Sadoulet (2018), Fuglie et al. (2020) and Seven and Tumen (2020) have been conducted on issues relating to agricultural productivity. The literature has documented that many farmers in developing countries are below their production frontiers, indicating that there is room to increase agricultural productivity above existing levels, even without a change in their current levels of input use (Liverpool-Tasie et al., 2011; Fuglie et al., 2020). Understanding the factors that hinder or accelerate agricultural productivity and how this may contribute to inclusive transformation and poverty reduction are therefore critical policy issues. Therefore, a deeper understanding of the drivers of agricultural productivity, and what is constraining it, hence remains critical in providing for basic human welfare, reducing extreme poverty, maintaining food security, and achieving social stability in transforming economy.

This study adopted Johansen Fisher Panel cointegration test for existence of long run relationship among the variables. Johansen proposes two different approaches; one of them is the likelihood ratio trace statistics and the other one is maximum Eigenvalue statistics, to determine the presence of cointegration vectors in non-stationary time series and panel data. For the trace tests the null hypothesis of at most "r" cointegration vector against the alternative hypothesis of full rank $r = n$ cointegration vector, the null and alternative hypothesis of maximum Eigenvalue statistics is to check the r cointegrating vectors against the alternative hypothesis of $r + 1$ cointegrating vectors. Thus the hypothesis formulated for this study is:

Null hypothesis (H_0): There is no cointegration among the variables

Alternative hypothesis (H_a): There is cointegration among the variables

The main objective of this study is to examine the drivers of agricultural productivity and its implication for economic growth; thus, this study isset out to:

i) evaluate the economy (GDP) reaction to structural shocks in agricultural productivity in transforming economy between 1980 and 2014;
ii) determine the drivers of agricultural productivity in transforming economy between 1980 and 2014.

MATERIALS AND METHODS

This study employed panel data covering thirty five (35) year period of 1980 to 2014. The data were sourced from World Bank's World Development Indicators (WDI), Penn World Table, United States Department of Agriculture (USDA) and Statistics on Public Expenditure for Economic Development (SPEED). For the purpose of this research work, the transforming countries with regular and complete data required

Table 1. Agricultural Productivity Index of selected transforming countries (base year: 2014 = 100)

Country / Year	1980	1990	2000	2010	2011	2012	2013	2014
Algeria	43.7	50.93	58.59	86.68	91.72	94.46	103.47	100
Armenia	47.61	47.5	58.16	80.55	89.91	96.89	98.51	100
Bangladesh	75.41	69.34	78.09	95.1	97.07	97.43	97.97	100
Belarus	60.55	69.37	67.57	94.22	90.88	96.6	93.58	100
Belize	87.22	85.38	121.8	104.44	95.24	108.79	95.71	100
Bhutan	120.81	115.19	115.03	107.38	116.64	106.61	96.97	100
Bolivia	100.43	105.63	112.98	94.62	92.65	99.97	96.82	100
China	34.95	43.52	65.16	85.6	89.73	93.13	96.11	100
Dominican Republic	63.99	56.5	67.69	89.14	87.32	90.37	98.21	100
Ecuador	79.6	85.44	100.13	108.97	105.62	106.11	98.56	100
Egypt	52.8	62.62	80.14	91.65	93.8	99.93	96.6	100
El-Salvador	87.24	79.5	87.65	94.41	95.08	102	101.21	100
Fiji	137.05	132.05	117.64	91.25	104.58	96.17	98.99	100
Georgia	131.42	127.67	111.85	93.23	98.72	90.45	104.69	100
Guatemala	48.4	55.61	66.62	84.32	85.49	93.26	97.86	100
Guinea	112.81	122.52	110.27	102.22	104.18	101.19	100.11	100
Guyana	61.42	48.14	74.25	83.57	89.19	88.29	93.87	100
Honduras	69.35	64.27	72.65	92.07	95.74	99.97	97.68	100
India	60.39	70.44	77.58	90.61	95.26	96.08	98.92	100
Indonesia	62.77	65.61	70.72	93.01	93.08	98.7	98.45	100
Jamaica	72.11	78.15	79.9	95.8	97.54	101.03	97.37	100
Kyrgyzstan	61.37	65.22	94.46	100.86	101.89	101.03	102.33	100
Malaysia	42.9	57.87	69.56	93.32	100.76	99.33	100.31	100
Moldova	79.86	87.25	80.88	109.51	106.25	87.37	96.2	100
Mongolia	108.66	102.75	131.71	102.85	96.4	99.17	101.41	100
Morocco	47.26	64.69	60.81	100.73	102.81	96.32	99.52	100
Paraguay	100.08	117.56	85.74	100.06	97.65	81.57	103.93	100
Peru	53.71	58.71	76.14	95.68	95.91	100.68	100.65	100
Philippines	70.79	74.44	79.71	96.54	97.96	99.4	100.07	100
Sao-Tome Principe	76	59.8	98.41	94.8	92.16	93.52	91.61	100
Senegal	78.91	99.07	104.28	118.28	90.08	102.85	97.12	100
Sri Lanka	100.62	90.11	95.8	108.4	101.25	105.86	112.81	100
Suriname	98.2	84.01	69.7	94.34	91.99	95.59	96.24	100
Thailand	59.42	55.95	74.65	86.82	92.98	100.51	100.04	100
Tunisia	75.78	93.27	89.87	98.36	97.22	107.91	108.02	100
Turkey	65.3	69.22	79.65	96.35	102.51	103.4	103.23	100
Ukraine	57.99	67.57	65.77	77.06	81.14	77.21	86.81	100
Uruguay	61.24	73.56	82.97	99.28	97.47	91.15	94.32	100
Uzbekistan	80.07	68.22	74.03	91.19	94.27	95.92	98.92	100
Viet Nam	50.7	59.16	73.26	90.21	93.71	99.08	99.2	100
Zimbabwe	118.56	122.14	143.34	120.28	113.68	119.19	114.65	100

Source: USDA-ERS (2018)

for this study were selected. Thus, the data focused on Agricultural Productivity (AP), Government Agricultural Expenditure (EXP), Agricultural Trade Barrier (ATB), Consumer Price Index (CPI), Farm Machinery (MACH), Fertiliser Consumption (FERT), Human Capital (HCAP), and Irrigation (IRRG).

Table 1 shows the agricultural productivity index of selected transforming countries. The selection is based on the World Development Report (2008) by the World Bank, which classifies countries according to the contribution of agriculture to economic growth and the share of the poor in the rural sector. This

Table 2. Data description and sources of data

Variable code	Variable name	Functional description of the variables	Unit of measurement	Sources
AP_t	Agricultural Productivity	Proxy by Agricultural Total Factor Productivity index	Index (2014=100)	USDA-ERS, 2018
EXP_t	Government Agricultural Expenditure	Outflow of resources from government to agricultural sector of the economy	Constant 2005 US dollar	SPEED, 2015
ATB_t	Agricultural Trade Barrier	Proxy by Net barter terms of trade (percentage ratio of the export unit value indexes to the import unit value indexes)	Index (2000 = 100)	World Bank's World Development Indicators (WDI), 2017
CPI_t	Consumer Price Index	Change in purchasing power of a currency and the rate of inflation.	Index (2000 = 100)	USDA-ERS, 2015
$HCAP_t$	Human Capital	Human capital index, based on years of schooling and returns to education	Index	Penn World Table, 2015
$MACH_t$	Farm Machinery	The total stock of farm machinery in 40 CV Tractor-Equivalents in use	Number	USDA-ERS, 2018
$FERT_t$	Fertilizer Consumption	Metric tonnes of fertiliser consumption measured in "N-fertilizer equivalents"	Metric tons	USDA-ERS, 2018
$IRRG_t$	Irrigation	Area equipped for irrigation (Supply of water to crops to help growth)	Hectares	USDA-ERS, 2018
GDP_t	Real Gross Domestic Product	GDP is an inflation adjusted measure that reflects the value of all goods and services produced by an economy in a given year, expressed in base-year prices (constant-price)	Constant 2010 US dollar (Millions)	World Bank's World Development Indicators (WDI), 2017.

classification was also adopted by Osinowo and Sanusi (2018), thus, "transforming" economies is a country where agriculture contributes less than 20% to Gross Domestic Product (GDP) and more than half of the poor live in rural areas. Table 2 shows in details description, sources and unit of measurement of the data used, while Figure 1 shows descriptive statistics (trend analysis) of the data.

This study employed Impulse Response Function (IRF) to evaluate the l_n (GDP) reaction to structural shocks in l_n (AP). The drivers of agricultural productivity (AP) in transforming economy was analysed using panel least square (fixed and random effects) as used by Osinowo and Sanusi (2018) and Atif et al. (2011).

Impulse Response Function (IRF)

Impulse Response Function shows the effect of shocks on the adjustment path of the variables. It describes the evolution of the variables of interest along a specified time horizon after a shock in a given moment (Osinowo and Sanusi, 2018). IRFs show the reactions of the variables to a unitary shock of one standard deviation (Schalck, 2007). IRFs are typically illustrated by graphs that provide a visual representation of responses, it also allows us to examine dynamic interactions among variables and the feedback effects on each other (Davytan, 2014). The IRF model is specified as:

$$l_nAP_t = \alpha_1 + \alpha_2 l_nGDP_{t-1} + \alpha_3 l_nAP_{t-1} + \varepsilon_1 \quad \text{(i)}$$

$$l_nGDP_t = \alpha_4 + \alpha_5 l_nAP_{t-1} + \alpha_6 l_nGDP_{t-1} + \varepsilon_2 \quad \text{(ii)}$$

Where:

AP_t...............Agricultural Productivity

GDP_t...........Real GDP

$\varepsilon_1 + \varepsilon_2$ ....residual of AP and real GDP

l_n ....logarithm form

A positive shock is given to the residuals (that is ε_1 and ε_2) of the above VAR model to see the response of the variable to each other. The structural shocks, which are considered as one-standard deviation to the variables, are recovered and they get their natural economic meaning. The IRF was identified by the Cholesky decomposition, which requires imposing the ordering of the variables that describe the contemporaneous relations among them. Thus, we need to specify the ordering of the variables that have economic reasoning behind it.

Panel Least Square

Basically, we have two types of panel models, fixed effects (FE) and random effects (RE) depending upon the assumptions about the error terms. The panel regression equation for this study is specified below:

$$l_nAP_t = \alpha_0 + \alpha_1 l_nEXP_t + \alpha_2 l_nATB_t + \alpha_3 l_nCPI_t + \alpha_4 l_nHCAP_t + \\ + \alpha_5 l_nMACH_t + \alpha_6 l_nFERT_t + \alpha_7 l_nIRRG_t + U_t \quad \text{(iii)}$$

Where:

AP_t .... Agricultural Productivity (index)
EXP_t .... Government Agricultural Expenditure (constant 2005 US dollar)
ATB_t .... Agric Trade Barrier (index)
CPI_t........... Consumer Price Index (index)
$HCAP_t$...... Human Capital (index)
$MACH_t$.... Farm Machinery (number)
$FERT_t$....... Fertiliser Consumption (metric tons)
$IRRG_t$ .... Irrigation (hectares)
U_t.............. Error term; all in time t (between-country error)
l_n .... logarithm form
t .... 1980 to 2014.

Equation (iii) is the fixed-effects panel data estimation of the model. Data for each country on the above mentioned eight variables were taken and transformed to logarithms, this will make interpretation of the results, such as elasticity, more economically meaningful. There are forty one (41) cross-sectional units of transforming economies with 35 time periods. In all, there are 1,435 observations for this study.

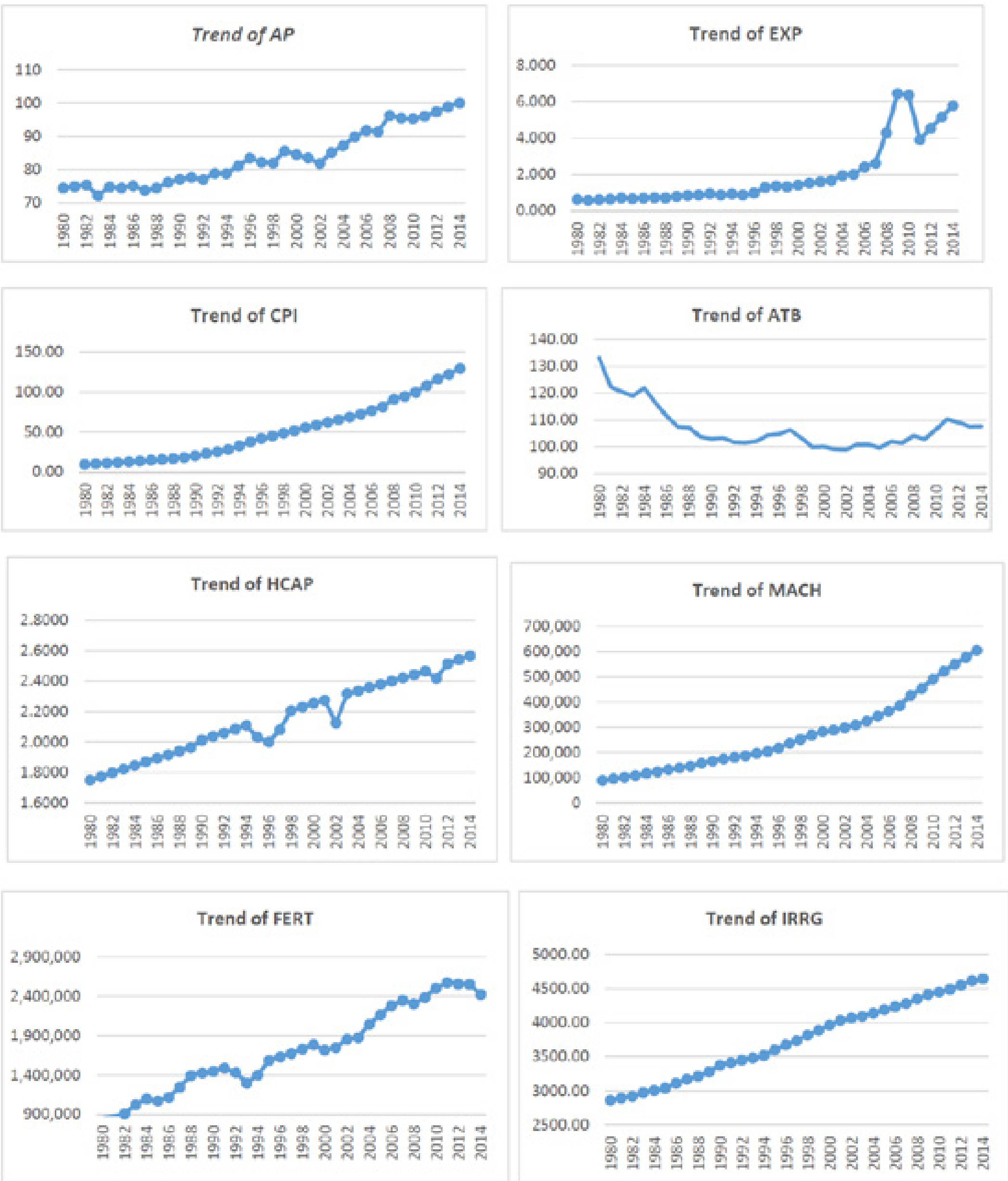

Figure 1. Descriptive Statistics (trend analysis) of the data.
Note: AP = Agricultural Productivity, EXP = Government Agricultural Expenditure, ATB = Agricultural Trade Barrier, CPI = Consumer Price Index, MACH = Farm Machinery, FERT = Fertiliser, HCAP = Human Capital and IRRG = Irrigation.

Fixed effects explore the relationship between predictor and outcome variables within an entity. Different variations with reference to cross-section or time are applied to the fixed effects models. The fixed effects (FE) model has constant slopes but intercepts differ according to the cross-sectional unit (Gujarati, 2003). FE with differential intercepts and slopes can also be applied on data, but inclusion of many variables and dummies may give results for which interpretation is cumbersome, because many dummies may cause the problem of multicollinearity (Gujarati, 2003).

The fixed-effects model controls for all time-invariant differences between the individuals, so the estimated coefficients of the fixed-effects models cannot be biased because of omitted time-invariant characteristics (Osinowo and Sanusi, 2018; Gujarati, 2003). One of the side effects of the features of this fixed-effects equation above is that it cannot be used to investigate time invariant causes of the dependent variables. Technically, time-invariant characteristics of the countries are perfectly collinear with the country (or entity) dummies. Basically, fixed-effects models are mostly designed to study the causes of changes within an entity. A time-invariant characteristic cannot cause such a change, because it is constant for each country.

In random effects, the variation across entities is assumed to be random and uncorrelated with the predictor or independent variables included in the model (Osinowo and Sanusi, 2018). The crucial distinction between fixed and random effects is whether the unobserved country effect embodies elements that are correlated with the regressors in the model. However, if it is assumed that differences across entities have some influence on the dependent variable, then a random-effects model is recommended. An advantage of the random effects over fixed effects is that one can include time-invariant variables, while in the fixed-effects model these variables are absorbed by the intercept. The random-effects model for equation (iii) above was specified as:

$$l_nAP_t = \alpha_0 + \alpha_1 l_nEXP_t + \alpha_2 l_nATB_t + \alpha_3 l_nCPI_t + \alpha_4 l_nHCAP_t + \\ + \alpha_5 l_nMACH_t + \alpha_6 l_nFERT_t + \alpha_7 l_nIRRG_t + e_i + U_t \qquad \text{(iv)}$$

Equation (iv) captures both the within-country and between-country errors unlike the fixed-effects model, which captures only the between-country error. In equation (iv) above, the within-country error was captured with U_t, while the between-country error was captured by e_i.

Hausman Specification Test

The most commonly used specification test for our model is Hausman specification test, which tests the null hypothesis that the coefficients estimated by the efficient random effects estimator are the same as the ones estimated by the consistent fixed effects estimator. The null hypothesis is that the preferred model is random effects and the alternative is fixed effects (Osinowo and Sanusi, 2018; Green, 2008). Hausman test basically tests whether the unique errors (*ui*) are correlated with the regressors.

If they are insignificant, then it is safe to use random effects. If we get a significant P-value, however, we should use fixed effects (Osinowo and Sanusi, 2018). The Hausman test is a kind of Wald $\chi2$ test with $k–1$ degrees of freedom (where k = number of regressors) as illustrated below:

$$W = (\beta_{FE} - \beta_{RE})'(V_{FE} - V_{RE})^{-1}(\beta_{FE} - \beta_{RE}) \qquad \text{(vii)}$$

H_0: errors (*ui*) are correlated
H_1: errors (*ui*) are not correlated

RESULTS AND DISCUSSION

Impulse Response Function (IRF) Analysis

The result of the IRF was presented in Figure 2. The two variables of interest (AP and GDP) were transformed to natural logarithms because this can transform the data to percentage changes and make interpretation of the results, such as elasticity, more economically meaningful. The horizontal axis in the graphs shows time period (a year, in this case). Points on the graph above zero display positive responses, while points below zero represent negative responses. The Figures show the 95% level of confidence from the confidence bands, the upper dotted line represents the upper confidence band, and while the lower dotted line represents the lower confidence band and the middle solid line (point estimate) shows IRFs.

By using the point estimate (the solid line) in Figure 2, the response of l_n (GDP) to a given shock of one standard deviation to the residual of l_n (AP) exerts a negative response. The negative response of l_n (GDP) to a given shocks in l_n (AP) in transforming economy was observed throughout the thirty fifth period. This result does not conforms to our *a priori* expectation that agricultural productivity can be a greater engine for driving growth in an economy. These findings contravene the earlier findings of Osinowo and Sanusi (2018) who found that agriculture can be the main engine for driving growth in an economy.

Panel Unit Root Test

The stationarity of the panel variables is conducted using the Levin-Lin-Chu test, this was adopted due to its simple methodology and alternative hypothesis

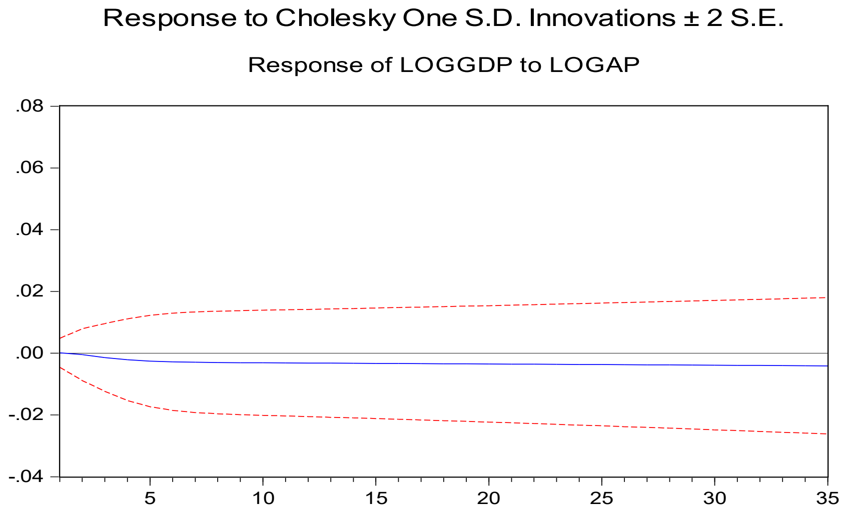

Figure 2. Impulse Reaction/ResponseFunctions of l_n (GDP) to l_n (AP) shock in transforming economy
NB: Solid lines: impulse response; dashed lines: 95% confidence bands

Table 3. Panel Unit Root Test

Variables	Level	First Difference	Order of Integration
AP_t	1.92039	-25.6472***	I(1)
ATB_t	-2.34665***	-	I(0)
CPI_t	-5.80712***	-	I(0)
EXP_t	2.07916	-22.1924***	I(1)
$FERT_t$	-3.65895***	-	I(0)
$HCAP_t$	-0.49297	-23.3230***	I(1)
$IRRG_t$	-5.65233***	-	I(0)
$MACH_t$	-4.06264***	-	I(0)

NB: (***) and (**) denote statistical significance at 1% and 5% level respectively
Source: Author's Computation (2017)

of heterogeneity (i.e. the persistence parameters are common across cross-section). The test was conducted for all the variables under observation and wherein the variable was not stationary, it was made possible by differentiating them. This is very important in the light of the recent development in econometric modeling which has revealed that estimators are inefficient if the variables in a panel data are nonstationary. Panel Unit Root test will helps to avoid spurious regression problem that can arise in panels when dealing with non-stationary variables. The results of the tests as reported in Table 3 showed that some variables are stationary at their levels, while others at their first difference.

Panel Cointegration Test

The result of the Johansen-Fisher Panel Cointegration as reported in Table 4 showed that for every case at 5% level of significance, we reject null hypothesis of no cointegration. Thus the case *p*-value 0.00 which is highly significance gives strong evidence that those variables have a long run relationship.

Fixed Effects and Random Effects Result

The results of both the fixed-effects model (iii) and random-effects model (iv) are presented in Table 5 for comparison purposes. However, the interpretation of empirical results is based on the fixed-effects model because of the outcome of the Hausman specification test, which points to the rejection of the null hypothesis, an indication that fixed-effects model is more appropriate and random effects is inconsistent. Taking a descriptive examination of the fixed-effects model as reported in Table 5, the estimated fixed effects coefficient of determination (R-squared) is 79.8. This indicates that the model explained about 79.8 percent of total variance in l_n (AP). The F-statistic result of the fixed effects with their probability value shows that these explanatory variables are jointly significant in explaining the variation in the dependent variable.

The findings of this study as reflected in Table 5 showed that l_n (ATB) has played an important role in promoting l_n (AP) in transforming economy. The result indicates that an increase in degree of trade restriction

Table 4. Johansen Fisher Panel Cointegration Test

Series	Hypothesized No. of CE(s)	Fisher Stat.* (from trace test)	Prob.	Fisher Stat.* (from max-eigen test)	Prob.
AP, ATB, CPI, EXP, HCAP, MACH, FERT, IRRG	None	966.4	0.0000	80.7	0.0000
	At most 1	535.6	0.0000	213.7	0.0000
	At most 2	62.2	0.0000	146.3	0.0000
	At most 3	239.1	0.0000	101.1	0.0000
	At most 4	157.3	0.0000	75.16	0.0001
	At most 5	104.3	0.0000	62.21	0.0022
	At most 6	71.77	0.0002	60.12	0.0038
	At most 7	60.36	0.0035	60.36	0.0035

* Probabilities are computed using asymptotic Chi-square distribution.
Source: Author's Computation (2017)

Table 5. Result of Fixed Effects Model (iii) and Random Effects Model (iv)

Variable	Fixed Effects	Random Effects
l_n ATB	0.053127**	0.047682**
	(2.138008)	(1.948737)
l_nCPI	0.006407	0.011956***
	(1.660531)	(3.243056)
l_nEXP01	0.000355	-0.000279
	(0.065658)	(-0.052299)
l_nFERT	-0.072970***	-0.063694***
	(-6.461097)	(-5.967933)
l_nHCAP	1.240893***	1.156573***
	(18.51498)	(21.46089)
l_nIRRG	0.077096***	0.066330***
	(2.881777)	(3.592481)
l_nMACH	-0.009612	-0.011029
	(-1.001413)	(-1.202716)
C	3.731159***	3.765947
	(15.34737)	(20.54304)***
R-squared	0.798147	0.666830
Adjusted R-squared	0.790139	0.663081
F-statistic	99.67618***	177.8453***
Hausman Test	46.062115***	

NB: (***) and (**) denote statistical significance at 1% and 5% level, respectively.
The numbers in parentheses are the t-statistics value.
Source: Author's Computation (2017)

of agricultural product from overseas will boost the level of agricultural productivity. The coefficient associated with l_n (ATB) is 0.0531, which is significant at 5 percent significance level. The results conform to *a priori* expectation and consistent with the findings of Eboh et al. (2012), who discovered that trade restriction on imported agricultural tradable commodities will boost agricultural Total Factor Productivity (TFP).

The coefficient of l_n (FERT) is negative and statistically significant at 1 percent significance level. The estimated coefficients signify that one percent increase in l_n (fertiliser) usage will lead to 0.0730 percent decrease in l_n (agricultural productivity). This observation does not conform to our *a priori* expectation because fertiliser is expected to boost agricultural productivity. This finding supports the earlier findings of Osinowo and Sanusi (2018) who revealed that continuous usage of inorganic fertiliser adversely reduce agricultural total factor productivity.

The coefficient of l_n (HCAP) was positive and statistically significant at 1 percent significance level. From the panel least regression analysis, it can be deduced that a one percent increase in the level of l_n (HCAP) will increase l_n (AP) level by around

1.2409 percent in transforming economy. This result supports the earlier findings of Nehru and Dhareshwar (1994), Sabir and Ahmed (2008) and Khalil and Anthony (2012). This result support endogenous growth literature, which showed that total factor productivity growth primarily driven by technological progress, innovation and increased investment in human capital, which includes education, skill and knowledge that enhance ability of labour to use new technologies more productively (Shittu and Odine, 2014).

The coefficient of l_n (IRRG) is positive and significant at 1% significance level. This study revealed that a 1% increase in l_n (irrigation) will increase the level of l_n (agricultural productivity) by about 0.0771%. This is in agreement with the findings of Srivastava et al. (2013) and Osinowo and Sanusi (2018). The coefficient of l_n (MACH) is negative but not significant at either 1 or 5% significance level.

CONCLUSION AND RECOMMENDATION

The study revealed that increase in the restriction of agricultural trade barrier l_n (ATB) will promote the level of agricultural productivity l_n (AP) in transforming economy. There is evidence of increased agricultural productivity with investment in human capital. The evidence provided in this study also confirmed that expansion in irrigation facilities will promote agricultural productivity in transforming economy.

RECOMMENDATIONS

The study found that l_n (agriculture trade barrier) increased l_n (agricultural productivity) and therefore recommends further trade restriction on imported agricultural tradable commodities, this will help to boost agricultural productivity in transforming economy.

The study confirmed a positive relationship between l_n (HCAP) and l_n (AP) and therefore recommends capacity building of the farmers at farm level. This will promote the quality of human capital which is crucial for improving crop, soil and water management, enhance the demand for and use of better and more efficient production inputs which will increase agricultural productivity.

The study revealed that l_n (irrigation) coefficient is positive and significant and therefore recommends investments in irrigation technologies. Increasing irrigation technologies and efficiency is expected to enhanced agricultural productivity in transforming economy.

CONFLICT OF INTEREST

The authors declared no conflicts of interest with respect to research, authorship and publication of this article.

ETHICAL COMPLIANCE

The authors have followed the ethical standards in conducting the research and preparing the manuscript.

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