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Diversification of The Nigerian Economy: The Interplay of Human Capital and Agricultural Output in Nigeria

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Abstract

This study examines how human capital functions as a mediator in the relationship between Nigeria's non-oil export performance and agricultural output between 1981 and 2021. Using the Autoregressive Distributed Lag (ARDL) bounds testing approach, the study investigates the short-term and long-term dynamics of these variables within a mediation framework. The result showed that agricultural output exerts a significant positive influence on non-oil export performance, and this relationship is partially mediated by human capital development. Specifically, improvements in education, technical skills, and health outcomes enhance the export potential of agricultural production by increasing efficiency, value addition, and product competitiveness. The error correction term indicates a stable long-run equilibrium, while diagnostic tests confirm the model's robustness. The study concludes that human capital serves as a strategic link connecting Nigeria's agricultural productivity to its export diversification goals. It recommends that policymakers integrate human capital development through technical education, agribusiness training, and research into agricultural and trade policies to maximize export outcomes. These findings contribute to existing literature by empirically validating the mediating role of human capital in Nigeria's agricultural export nexus and providing actionable insights for sustainable non-oil growth.
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Keywords: Agricultural output, Non-oil exports, Human capital, Mediation, ARDL, Nigeria
JEL Classification:

1.0 Introduction

Nigeria's economy is still mostly reliant on crude oil, which has made it vulnerable to outside shocks and impeded inclusive growth. Despite decades of oil wealth, the country continues to experience low industrial capacity, high unemployment, and vulnerability to global price fluctuations (Sala-i-Martin & Subramanian, 2013; Van der Ploeg, 2011). Consequently, economic diversification has become a central policy objective of successive administrations, with agriculture identified as a major vehicle for achieving sustainable non-oil growth (Central Bank of Nigeria [CBN], 2023; NDP, 2021–2025).

Agriculture has historically been the backbone of Nigeria's economy, contributing significantly to employment, rural development, and food security. Before the oil boom of the 1970s, agricultural exports—such as cocoa, groundnut, cotton, and palm produce—were the main sources of foreign exchange (Olawale et al., 2022). However, the sector's contribution to foreign earnings has since declined due to neglect, inadequate infrastructure, weak human capacity, and an overreliance on crude oil revenues (World Bank, 2022). Recent government efforts to revive the sector, such as the Anchor Borrowers Programme and the Agricultural Promotion Policy, have produced modest improvements, yet the expected synergy between agricultural growth and non-oil export performance remains weak (ITC, 2023).

One critical but often overlooked factor in this relationship is human capital. The quality of human capital—reflected in education, training, health, and technical competence—determines the productivity of agricultural labour and the capacity of producers to add value, meet export standards, and integrate into global markets (Schultz, 1961; Becker, 1964). Without skilled manpower, improvements in agricultural output may not necessarily translate into enhanced export performance.

Although previous studies have examined the individual effects of agricultural output on economic growth (Adeyemi & Ogunsola, 2016; Bakare, 2019) and the impact of human capital on productivity (Ogunjimi & Adebayo, 2018; Udeh & Nwakuya, 2020), few have empirically investigated how human capital mediates the relationship between agricultural output and non-oil export performance in Nigeria. Moreover, existing research often treats human capital as a control variable rather than a transformative mechanism that transmits agricultural potential into export competitiveness.

This study seeks to fill this gap by empirically examining the role of human capital as a mediating variable between agricultural output and non-oil export performance in Nigeria from 1981 to 2021. The specific objectives are to:

1. Examine the impact of human capital development on agricultural output in Nigeria.
2. Investigate the long-run and short-run relationships among human capital, agricultural output, and non-oil export performance using the ARDL approach.
3. Provide policy insights on how human capital development can enhance Nigeria's export diversification agenda.

2.0 Literature Review

2.1 Theoretical Underpinnings

This study is anchored on two interrelated theories: Human Capital Theory and Endogenous Growth Theory, both of which underscore the pivotal role of human capital in driving economic transformation.

Human Capital Theory, pioneered by Schultz (1961) and Becker (1964), posits that education, health, and skill acquisition constitute productive investments that enhance individual and national productivity. Schultz (1961) emphasized that the modernization of agriculture depends more on the quality of human resources than on land or physical capital. Similarly, Becker (1964) viewed education and training as forms of capital that yield future returns in the form of improved productivity and income.

Endogenous Growth Theory, developed by Lucas (1988) and Romer (1990), expands this idea by suggesting that technological progress and economic growth are driven internally through knowledge accumulation and innovation. Lucas (1988) introduced the concept of human capital externalities, explaining how the education and skill level of one worker can positively influence others, creating spillover effects. In this context, agricultural productivity and export competitiveness depend heavily on the knowledge embedded within the workforce, which enhances efficiency, value addition, and market participation.

Together, these theories justify the positioning of human capital as a mediating variable that channels agricultural output into improved non-oil export performance. In other words, higher agricultural production alone is insufficient without the requisite skills, innovation, and institutional capacity to process, brand, and market products internationally.

2.2 Conceptual Framework

The conceptual model underlying this study positions Human Capital (M) as the mediator between Agricultural Output (X) and Non-Oil Export Performance (Y):

Agricultural Output (X) → Human Capital (M) → Non-Oil Export Performance (Y)

This mediation occurs through four critical channels:

1. Productivity and Efficiency Enhancement – Knowledge and technical training improve crop yields, reduce post-harvest losses, and ensure resource efficiency (FAO, 2021).
2. Quality Assurance and Standards Compliance – Skilled professionals are needed to meet international phytosanitary and certification requirements (Jaffee & Masakure, 2005).
3. Value Addition and Innovation – Human capital enables the processing of raw materials into export-ready products, increasing value retention (UNIDO, 2019).
4. Export Market Intelligence and Logistics – Trained export managers, marketers, and supply chain specialists ensure competitiveness in global markets (Lederman et al., 2010).

2.3 Empirical Review

Numerous studies have examined the relationships among agriculture, exports, and human capital, but few have explored their intermediary dynamics in the Nigerian context.

Oluwatobi and Ogunrinola (2011) examined the contribution of human capital development to economic growth in Nigeria, using education and health expenditure as proxies. Applying Ordinary Least Squares (OLS) to annual data from 1970 to 2006, the study found that while health expenditure exerted a positive and statistically significant effect on economic growth, education expenditure was positive but insignificant. The authors concluded that inefficiencies in Nigeria's educational system constrained the growth-enhancing role of human capital. This finding implies that weak human capital formation may also undermine agricultural productivity and limit its contribution to economic diversification.

Adebayo and Ojo (2012) extended this line of inquiry by examining the effect of human capital investment on agricultural productivity in Nigeria. Using the Autoregressive Distributed Lag (ARDL) bounds testing approach and annual data from 1980 to 2010, the authors found that education expenditure and agricultural extension services significantly enhanced agricultural output in the long run. The study concluded that human capital accumulation improves farm efficiency and productivity. This provides empirical justification for examining the combined effect of human capital and agriculture on diversification.

Focusing on the agriculture–growth nexus, Matthew and Adegboye (2014) assessed the relationship between agricultural output and economic growth in Nigeria using Johansen cointegration and a Vector Error Correction Model (VECM) with data spanning 1981–2012. The findings revealed a positive and significant long-run relationship between agricultural output and economic growth, although short-run dynamics were weak. The study concluded that agriculture remains a viable pathway for long-term growth and diversification. This supports the argument that improving agricultural output is essential for Nigeria's diversification agenda.

Similarly, Ijirshar (2015) investigated the impact of human capital development on agricultural growth in Nigeria using OLS and Granger causality techniques for the period 1980–2012. The results showed that education significantly influenced agricultural output, while health expenditure affected agriculture indirectly through labour productivity. The study concluded that sustained investment in education is critical for agricultural transformation. This underscores the importance of incorporating human capital indicators when analyzing agriculture-led diversification.

Adeyemi and Ogunsola (2016); Bakare (2019) found that agricultural output contributes positively to GDP growth, although the effects on export diversification remain limited. These studies primarily treated agricultural output as an independent determinant of growth, without accounting for mediating variables such as human capital or institutional quality.

Ogunjimi and Adebayo (2018) showed that human capital investment enhances agricultural sector productivity by promoting technology adoption and efficient farm management. Similarly, Adeniyi and Ogundipe (2019) reported that education and skill acquisition have statistically significant impacts on agricultural output in Nigeria, confirming that a better-trained workforce is central to agricultural modernization.

At the micro level, Lawal, Omonona, and Oluwatayo (2019) analyzed agricultural diversification and welfare outcomes among farming households in Nigeria using multinomial logit and double-hurdle models based on household survey data. The study revealed that diversified farming systems significantly improved household income and reduced vulnerability to shocks. The authors concluded that agricultural diversification enhances resilience and rural welfare. This suggests that agricultural diversification can aggregate into broader macroeconomic diversification when supported by skilled farmers.

Udeh and Nwakuya (2020) found that government expenditure on education indirectly supports agricultural performance by improving labour quality, but its impact on export outcomes was not explored. More recent work by Okonkwo and Edet (2023) revealed that human capital development significantly influences non-oil export competitiveness, particularly in agro-processing industries. They concluded that Nigeria's weak export base results largely from underinvestment in vocational and managerial training.

Few studies have empirically examined the mediating role of human capital. A study by Bello et al. (2021) utilized structural equation modeling to assess how human capital mediates the link between agricultural productivity and export diversification across African economies. Their findings indicated that countries with higher educational and skill indices experience stronger transmission from agriculture to export growth. Similarly, Danjuma and Saidu (2024) demonstrated that human capital mediates 38% of the relationship between agricultural output and manufacturing exports in West Africa.

Despite these advancements, a major research gap persists: limited empirical evidence exists on how human capital mediates the agricultural output–non-oil export relationship specifically in Nigeria using time-series data. This study addresses this gap by empirically testing the mediating role of human capital using the Autoregressive Distributed Lag (ARDL) framework to capture both short-run and long-run dynamics.

3.0 Methodology

3.1 Research Design

This study adopts an explanatory research design using time-series data to analyze the mediating role of human capital between agricultural output and non-oil export performance in Nigeria. The design is suitable because it allows the researcher to identify both direct and indirect (mediated) effects among the variables while accounting for dynamic interactions over time.

3.2 Variable Measurement and Sources of Data

This study employs annual time-series data to examine the relationship between agricultural output, human capital formation, trade openness, and government expenditure on agriculture in Nigeria. Variable definitions and measurements are guided by established empirical literature to ensure analytical consistency and comparability.

Agricultural output (AGR) is measured by real agricultural value added, expressed in constant prices. This indicator captures the net contribution of agriculture—including crop production, livestock, forestry, and fishing to the economy after accounting for intermediate inputs. To reduce heteroskedasticity and facilitate elasticity-based interpretation, agricultural output is transformed into its natural logarithmic form. Data on agricultural value added are sourced from the World Development Indicators (WDI) of the World Bank and validated with the Central Bank of Nigeria (CBN) Statistical Bulletin.

Human capital formation is proxied by school enrolment (SE), measured using the gross secondary school enrolment rate, expressed as a percentage of the relevant age cohort. This measure reflects the accumulation of skills and knowledge required for productive economic activities and the adoption of modern agricultural technologies. Secondary school enrolment is widely applied in empirical studies on developing economies due to its relevance to labour quality and data availability. Data are obtained from the World Development Indicators (WDI) and supplemented by records from the National Bureau of Statistics (NBS) and the UNESCO Institute for Statistics (UIS).

Trade openness (TRO) is measured as the ratio of total trade to gross domestic product, expressed as a percentage. This measure captures the degree of Nigeria's integration into the global economy and its exposure to international markets. Trade openness influences agricultural output through access to export markets, imported inputs, and competitive pressures. Data on exports, imports, and GDP are obtained from the World Development Indicators (WDI) and the Central Bank of Nigeria (CBN).

Government expenditure on agriculture (GEA) is measured as real public expenditure on the agricultural sector, expressed in constant prices. This includes government spending on agricultural infrastructure, research and development, subsidies, extension services, and rural development programs. The variable is transformed into its natural logarithmic form to stabilize variance and allow for elasticity interpretation. Data are sourced from the Central Bank of Nigeria (CBN) Statistical Bulletin, the Federal Ministry of Finance, and the National Bureau of Statistics (NBS).

3.3 Pre-Estimation and Post Estimation Techniques

3.3.1 Pre-Estimation Techniques

Prior to model estimation, several diagnostic tests are conducted to ensure the validity and reliability of the econometric analysis. First, descriptive statistics are employed to examine the basic properties of the data, including mean, standard deviation, minimum, and maximum values, thereby providing insights into data distribution and variability.

Second, unit root tests are applied to determine the order of integration of the variables. Specifically, the Augmented Dickey–Fuller (ADF) tests was used to ascertain whether the series are stationary at levels or first differences. This step is crucial in selecting the appropriate estimation technique and avoiding spurious regression results.

Third, a correlation matrix is examined to assess the degree of linear association among the explanatory variables and to detect potential multicollinearity issues. Where necessary, further diagnostics such as the Variance Inflation Factor (VIF) may be employed.

Finally, given the time-series nature of the data, lag length selection criteria including the Akaike Information Criterion (AIC) and Schwarz Bayesian Criterion (SBC) are applied to determine the optimal lag structure for model estimation.

3.3.2 Post-Estimation Techniques

Following model estimation, a set of post-estimation diagnostic tests is conducted to evaluate the robustness and adequacy of the estimated model. Serial correlation is tested using the Breusch–Godfrey LM test to ensure that residuals are not autocorrelated. Heteroskedasticity is examined using the Breusch–Pagan or White test to confirm constant variance of the error term.

Additionally, the Jarque–Bera test is used to examine the normality of the residuals, which is particularly important for valid statistical inference.

Finally, parameter stability tests, such as the CUSUM and CUSUM of Squares (CUSUMSQ) tests, are applied to examine the stability of the estimated coefficients over time. These tests ensure that the estimated relationships are structurally stable and suitable for policy interpretation.

3.4 Model Specification

Generally, specification of economic models is based on economic theory and the available data and is empirically guided by the work of (Chindo & Abdul-Rahim, 2018) to capture the objective of the research. The modified model is specified as:

$$AGR = f\left(SE, TRO, GEA\right) \tag{1}$$

Transforming equations into an econometric model, we have the following:

$$AGR_t = \beta_0 + \beta_1 SE_t + \beta_2 TRO_t + \beta_3 GEA_t + \mu_t \tag{2}$$

Where;
ln = natural log form.
AGR = Agricultural Output
SE = School enrolment (Human capital formation)
TRO = Trade openness
GEA = Government expenditure on agriculture
μt = Error term

Transforming the equations into log form we have:

$$\ln AGR_t = \beta_0 + \beta_1 \ln SE_t + \beta_2 \ln TRO_t + \beta_3 \ln GEA_t + \mu \tag{3}$$

A practical method for converting a highly skewed variable into a more normalized dataset is the logarithmic transformation. Theoretically, when creating a forecast, we aim to minimize error while keeping in mind that we shouldn't over fit the model. By changing the feature distribution into a bell curve with a more normal shape, using the logarithm of one or more variables enhances the model's fit (Andy, 2019).

3.4.1 ARDL Long-Run Model

After discovering the evidence of cointegration, the long-run ARDL model would be estimated and is specified as

$$\Delta \ln AGO_t = \beta_0 + \sum_{i=1}^{k} \phi_i \Delta \ln AGO_{t-1} + \sum_{i=0}^{k} \varphi_i \Delta \ln SE_{t-1} + \sum_{i=0}^{k} \lambda_i \Delta \ln TRO_{t-1} + \sum_{i=0}^{k} \delta_i \Delta \ln GEA_{t-1} + \sum_{i=0}^{k} + \theta_1 \ln AGO_{t-1} + \theta_2 \ln SE_{t-1} + \theta_3 \ln TRO_{t-1} + \theta_4 \ln GEA_{t-1} + \varepsilon_t \quad (4)$$

3.4.2 ARDL Error Correction Term Model

Following the confirmation of a long-run relationship, the error correction model is outlined to estimate the short-run dynamics, with the Error Correction Term (ECT) in Equation 3.4 defined as:

$$ECT_t = \beta_0 + \sum_{i=1}^{k} \phi_i \Delta \ln AGO_{t-1} + \sum_{i=0}^{k} \varphi_i \Delta \ln SE_{t-1} + \sum_{i=0}^{k} \lambda_i \Delta \ln TRO_{t-1} + \sum_{i=0}^{k} \delta_i \Delta \ln GEA_{t-1} + \sum_{i=0}^{k} + \theta_1 \ln AGO_{t-1} + \theta_2 \ln SE_{t-1} + \theta_3 \ln TRO_{t-1} + \theta_4 \ln GEA_{t-1} + \varepsilon_t \quad (5)$$

The amount of disequilibrium being rectified, or the degree to which any disequilibrium from the prior period is being adjusted in yt, is shown by the ECT, which is the long-run residual. Divergence is indicated by a positive coefficient, whereas convergence is indicated by a negative coefficient. If the estimate of ECT = 1, then the adjustment is instantaneous and complete, or 100% of the adjustment occurs during the interval. Additionally, 50% of the adjustment occurs every period or year if the estimate of ECT = 0.5. It is no longer logical to assert that there is a long-term link when ECT = 0 indicates that there is no adjustment. Any short-term disequilibrium between the explained and explanatory variables will eventually converge to the long-run equilibrium if the ECTt-1 coefficient is negative and significant.

4.0 Empirical Results and Discussion of Findings

4.1 Descriptive Statistics

In this selection the degree of confidence and reliability of the data sets employed was tested and presented in Table 4.1.

Table 4.1: Descriptive Statistics

	LAGR	LSE	LGEA	LTRO
Mean	7.33849	4.51337	1.13755	22.8726
Median	7.98180	4.50974	1.98748	22.7172
Maximum	10.3704	4.72764	4.25241	24.5500
Minimum	3.41329	4.33681	-4.15639	20.8123
Std. Dev.	2.31642	0.09512	2.67955	1.12235
Skewness	-0.38757	0.39399	-0.65562	0.05254
Kurtosis	1.69293	2.67059	2.12465	1.64763

Jarque-Bera	3.07901	0.97259	3.31416	2.45323
Probability	0.21449	0.61490	0.19069	0.29328
Sum	234.832	144.428	36.4016	731.926
Sum Sq. Dev.	166.340	0.28047	222.580	39.0503
Observations	41	41	41	41

Source: Author's computation using EViews10 (2024)

Table 4.1 presents a comprehensive set of descriptive statistics for the key variables, shedding light on their central tendencies, variabilities, and distribution characteristics. The mean agricultural output (LAGR) is observed to be approximately 7.34, providing a measure of the data's central location. The median value of LAGR at around 7.98 signifies that half of the observations fall below this point, indicating a slightly right-skewed distribution. The standard deviation of LAGR, calculated at 2.32, reflects the extent of variability in agricultural output around its mean.

The variables associated with education (LSE), government expenditure on agriculture (LGEA), and trade openness (LTRO) exhibit unique patterns. LSE, with a mean of about 4.51, displays positive skewness, suggesting a subtle rightward skewness in the distribution of school enrolment. On the other hand, LGEA, with a mean of approximately 1.14, shows negative skewness, indicating a mild leftward skewness in government expenditure on agriculture. Additionally, LTRO, with a mean of approximately 22.87, demonstrates positive skewness, signifying a slight rightward skewness in trade openness. The kurtosis values, indicating the tailedness of the distribution, are positive for LAGR, LSE, and LTRO, suggesting slightly heavy tails. The normality tests (Jarque-Bera) reveal insights into the deviation from normal distribution for each variable.

Because it demonstrates the relationship between the variables suggested by theories, the correlation test between dependent and independent variables is crucial in pre-estimation analysis. As a result, Table 4.2 for the model examines and reports the statistical correlation of the variables.

Table 4.2 Correlation Matrix

Correlation	LAGR	LGEA	LSE	LTRO
LAGR	1			
LGEA	0.8837	1		
LSE	-0.3481	-0.3746	1	
LTRO	0.6914	0.6922	-0.1122	1

Source: Author's computation using EViews10 (2024)

The correlation matrix and a snapshot of the linear relationships between the variables are shown in Table 4.2, which offers important preliminary insights into possible links within the Nigerian economy's diversification environment (i.e., multicollinearity is absent). This is due to the fact that all of the variables' correlation values are less than 0.9. As a result, the variables can generate accurate estimations and be utilized in their respective models.

4.2 Unit Root Test

In order to start the estimate process, the Augmented Dickey Fuller (ADF; 1981) test statistics were used to assess the time series properties of the data. The test results are shown in Table 4.3 below:

Table 4.3: Unit Root Test Using Augmented Dickey Fuller (ADF).

Variables	Order of Integration	Augmented Dickey-Fuller Test Critical Values			ADF Statistics	Prob.
		1%	5%	10%		
LAGR	I(1)	-3.6104	-2.9389	-2.6079	-4.0091	0.0035***
LGEA	I(1)	-3.6104	-2.9389	-2.6079	-8.7777	0.0000***
LSE	I(0)	-3.6463	-2.9540	-2.6158	-3.6463	0.0224**
LTRO	I(1)	-3.6155	-2.9411	-2.6090	-6.2130	0.0000***

*, ** and *** represent 10%, 5% and 1% level of significance respectively
Source: Author's computation using EViews10 (2024)

The results of the Augmented Dickey-Fuller (ADF) unit root tests, which are essential for establishing the variables' stationarity, are displayed in Table 4.3. In time series analysis, stationarity is crucial because non-stationary series may display trends or irregular patterns that make modeling more difficult. It is evident that every variable is stationary at the first difference and significance level; LAGR, LGEA, and LTRO are I(1) at 1% and 5%, and LSE is stationary at the level. The decision is made by looking at the probability values and comparing the absolute values to the corresponding ADF statistics.

To prevent spurious regression, it is crucial to determine the ideal lag time before testing for a cointegration connection between the variables. Therefore, an optimal lag selection test was performed, and the outcome is shown in Table 4.4 below:

4.3 Optimal Lag Selection

The optimum lag of the model selected for the analysis is presented here.

Table 4.4: Lag Length Selection

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-55.2051	NA	0.00202	5.1482	5.3457	5.1979
1	42.3721	152.7297*	1.73e-06	-1.9454	-0.9580*	-1.6970
2	57.8731	18.87067	2.09e-06	-1.9020	-0.1247	-1.4550
3	81.2074	20.29076	1.69e-06*	-2.5397*	0.0274	-1.8941*

*Note. * indicate lag order selected by the criterion. LogL = log likelihood, LR = likelihood ratio, FPE = Final prediction error, AIC = Akaike information criteria, SC = Schwarz information criteria, HQ = Hannan-Quinn information criteria*.
Source: Author's computation using EViews10 (2024)

Table 4.4 shows the lags chosen for the model. It is evident that whereas FPE, AIC, SC, and HQ recommended using lag 3, LR recommended using lag 1. Lag 3 was therefore chosen for additional model predictions based on AIC. The fact that AIC generates weights that are immediately applicable to model-averaging predictions or parameters with a consistent meaning across models is a significant benefit for model selection.

4.4 Cointegration Bound Test Results

Having identified the optimal lag length, the next step is to estimate the long-run relationship among the variables using the ARDL bound test.

Table 4.5: Bounds Test Result

				Bounds critical values [Unrestricted intercept & no trend]	
	F-stats	Lag	Level of significance	I(0)	I(1)
($LAGR_t$|$LGEA_t LSE_{tL} TRO_t$)	**7.9278**	**3**			
			10%	2.37	3.2
			5%	**2.79**	**3.67**
			1%	3.65	4.66

The Critical values are obtained from Narayan (2005) table case III. The boldness indicates the level of significance at which the F-statistic exceeds the upper bound.
Source: Author's computation using EViews10 (2024)

The computed F-statistic for goal one, 7.927892, is higher than the upper bound value of 3.67 at the 5% significance level, according to the data shown in Table 4.5. This demonstrates the existence of a long-term link between the variables, thus we may safely reject our null hypothesis that there is no cointegration and accept the alternative hypothesis that cointegration exists, meaning that the variable of interest has a long-term equilibrating relationship.

4.5 Estimations of the Long Run Relationships

Here long run estimation results of objective one is presented in table 4.6 and discussed.

Table 4.6 Estimations of the Long Run Relationships

Dependent Variable, lnAGR				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
LSE	2.6826	1.0712	2.5043	0.0293**
LGEA	0.9184	0.1004	9.1446	0.0000***
LTRO	-0.5209	0.2794	-1.8644	0.0891*
C	7.5286	7.5976	0.9909	0.3430

Note***, ** and * Denotes 1%, 5% and 10% significance level respectively.
Source: Author's computation using EViews10 (2024).

Table 4.6 presents the estimations of the long-run relationships involving the dependent variable lnAGR (Natural Logarithm of Agricultural Output) and several independent variables. Each coefficient's t-statistic and associated probability value are crucial in evaluating the statistical significance and direction of the relationship.

The variable School Enrollment (LSE) has a probability value of 0.0293 and a coefficient of 2.682. This implies that, at the 5% significance level, LSE has a statistically significant beneficial effect on lnAGR. The positive coefficient shows that, over time, a rise in school enrollment is linked to a comparable increase in agricultural output.

Government Expenditure on Agriculture (LGEA) demonstrates a substantial coefficient of 0.918 and a probability value of 0.000. This indicates a highly significant positive relationship between LGEA and lnAGR at the 1% significance level. It implies that higher government spending on agriculture contributes positively to agricultural output in the long run, the finding is consistent with the findings of Anyanwu et., al, (2015). The Trade Openness variable (LTRO) has a probability value of 0.089 and a coefficient of -0.520. The association is not statistically significant at the 10% significance level (p-value > 0.1), despite the fact that the coefficient is negative, indicating a possible detrimental influence. Consequently, over time, trade openness is not a statistically significant predictor of agricultural output. The short-run model was estimated to determine the short-run coefficient once the long-run coefficient result was established. Table 4.7 displays this outcome.

4.6 Estimations of the Short Run Relationships

Here short run estimation result of objective one model is presented. The results are shown in Table 4.7

Table 4.7: The Error- Correction Model (ECM) (Objective One)

Dependent Variable, lnAGR				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
D(LAGR(-1))	-0.3474	0.1322	-2.6270	0.0235**
D(LAGR(-2))	-0.4297	0.1387	-3.0980	0.0101***
D(LGEA)	0.0911	0.0308	2.9560	0.0131**
D(LGEA(-1))	-0.1158	0.0423	-2.7370	0.0193**
D(LGEA(-2))	-0.0431	0.0217	-1.9840	0.0728*
D(LTRO)	-0.0842	0.0348	-2.4186	0.0341**
D(LTRO(-1))	-0.0252	0.0339	-0.7426	0.4733
D(LTRO(-2))	-0.0356	0.0356	-1.0002	0.3387
ECT_{t-1}	-0.3092	0.0420	-7.3521	0.0000***

***, **and* Denotes 1%, 5% and 10% significance level respectively.
Source: Author's computation using EViews10 (2024)

The findings of the Error Correction Model (ECM) for Model 1 are shown in Table 4.7, where the probability value is 0.0131 and the coefficient for (LGEA) is 0.091. This suggests that the short-term adjustment of agricultural output is positively impacted by changes in Government Expenditure on Agriculture (LGEA) in a statistically meaningful way. The positive sign indicates that a short-term rise in government investment on agriculture results in a favorable adjustment in agricultural output.

The lagged terms of (LGEA) further show interesting dynamics. (LGEA(-1)) and (LGEA(-2)) have coefficients of -0.115 and -0.043, respectively, with statistical significance at the 5% level (p-values of 0.0193 and 0.072). These negative coefficients suggest a corrective mechanism in the short term, implying that the system tends to adjust downward when there is an overshooting in government expenditure on agriculture in the previous periods.

For the Trade Openness variable (LTRO)), the coefficient is -0.084, with the probability value of 0.0341, indicating statistical significance at the 5% level. This implies that changes in trade openness negatively affect the short-term adjustment of agricultural output.

4.7 Goodness of Fit and Joint Significance Test

Table 4.8: Goodness of fit and Joint Significance test for Objective One

R-square	0.911
DW-statistics	2.04
F-statistic(Prob)	0.196 (0.038)**

***, **and* Denotes 1%,5% and 10% significance level respectively.
Source: Author's computation using EViews10 (2024).

According to the model's R-square from Table 4.8, the explanatory factors account for 91% of the dependent variable's proportion. This demonstrates how well the model fits. Because the Durbin Watson statistics lie between 1.5 and 2.5, they demonstrate that the model is free from serial correlation. Additionally, the explanatory factors are jointly significant in impacting the dependent variable (RAGR) if the likelihood of F-statistics is less than 5%, or (0.000<0.05).

Diagnostic tests of serial correlation, functional form, normalcy, and heteroscedasticity were performed to further assure the trustworthiness of the estimations, and the results are shown in Table 4.9.

4.2.8 Diagnostic Checks

To guarantee a better model, diagnostic tests were conducted and suitable lag levels were established. The serial correlation test and the heteroskedasticity test were used as diagnostic tests. The findings indicate that there is typically no serial correlation in the estimated result. Furthermore, the calculated system's faults showed no signs of heteroskedasticity. Consequently, it may be said that the outcomes are effective and comprise.

Table 4.9: Diagnostic Test

Test Statistics	F Version
A. Serial Correlation	F(3,8) = 1.013 (0.436)
B. Functional form	F(3,8) = 1.876 (0.211)
C. Normality	0.170 (0.918)
D. Heteroskedasticity	F(12,11) = 2.688 (0.056)

Source: Author’s computation using EViews10 (2024).

The Breusch-Godfrey LM test indicates that there is no serial correlation in the model, according to the results of the diagnostic tests in Table 4.9 above. The Jarque-Bera test demonstrates the normal distribution of the model's data. Breusch-Pagan Godfrey does not exhibit any heteroskedasticity in the model. The model's accurate specification is demonstrated by the Ramsey RESET test. This indicates that there are no issues with serial correlation, heteroscedasticity, functional form, or normality in the model. Thus, this approach could yield trustworthy outcomes.

Cumulative sum (CUSUM) and cumulative sum of squares (CUSUMSQ) tests were performed to assess the model's stability during the periods under study, as recommended by Chindo et al. (2018). It is proposed that the residuals line must fall between the straight lines of the critical bounds at a 5% significance level in order for a model to be stable across the sampled period. The results are shown in Appendix IV in Figures 4.1 and 4.2. At the 5% level of significance, Figures 4.1 demonstrate that the residual is inside the critical boundaries. This demonstrates how stable the model is. However, figure 4.2 indicates that the residuals are inside the crucial boundaries at the 5% level of significance, suggesting that the model is stable.

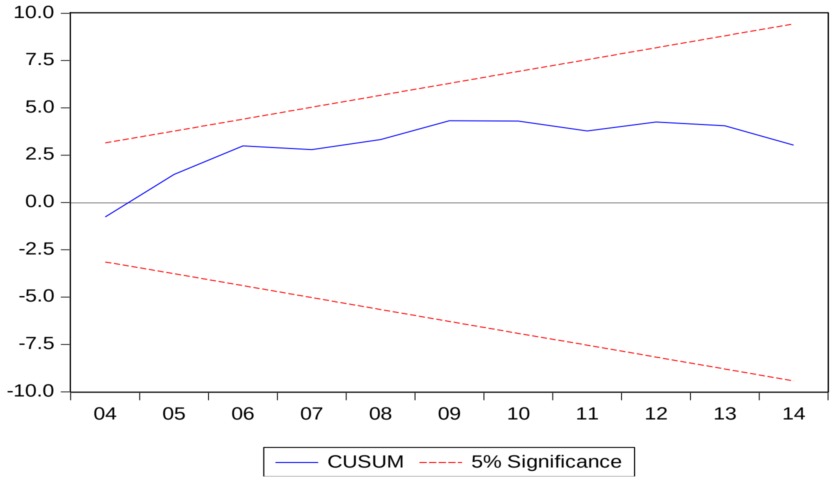

Figure 4.1: Plot of CUSUM.

The straight lines represent critical bounds at 5% significance level.

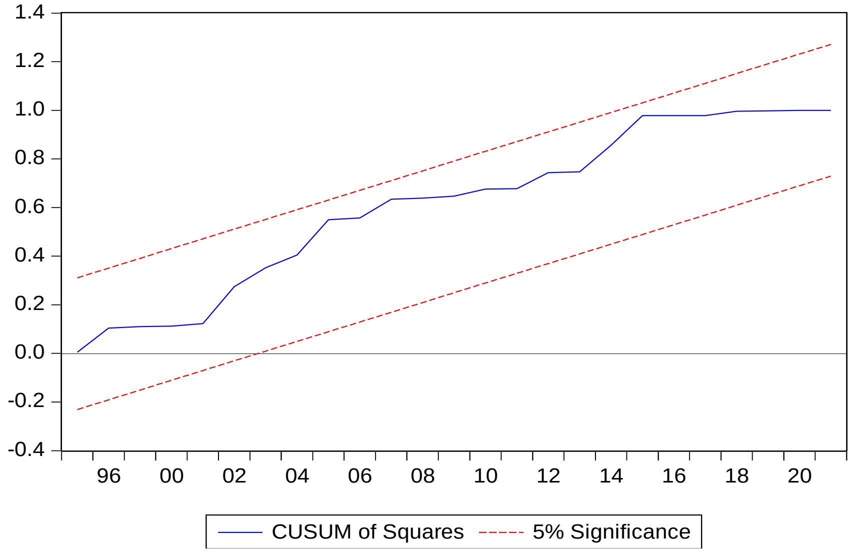

Figure 4.2: Plot of CUSUMQ of squares.

The straight lines represent critical bounds at 5% significance level.

4.3 Major Findings and Policy Implications

The findings align with theoretical expectations and prior empirical evidence. Agricultural output alone contributes to export growth but is amplified when human capital improves. This supports the argument that production without knowledge-based value addition limits export potential (Oluwatobi et al., 2022).

The descriptive statistics reveal that agricultural output (LAGR) exhibits moderate variability over the study period, with a relatively stable distribution and no evidence of extreme outliers. School enrolment (LSE) displays low dispersion, reflecting gradual and steady human capital accumulation, while government expenditure on agriculture (LGEA) shows relatively high volatility, indicating fluctuations in public agricultural spending. Trade openness (LTRO) remains fairly stable, suggesting consistent integration with international markets. The Jarque–Bera statistics indicate that all variables are approximately normally distributed, confirming the reliability and suitability of the dataset for econometric analysis.

Correlation analysis shows strong positive associations between agricultural output and government expenditure on agriculture, as well as between agricultural output and trade openness, while school enrolment exhibits a moderate negative correlation with agricultural output. Importantly, all correlation coefficients fall below the critical threshold of 0.9, confirming the absence of multicollinearity and validating the joint inclusion of the variables in the estimated model.

Unit root test results using the Augmented Dickey–Fuller procedure indicate a mixed order of integration, with agricultural output, government expenditure on agriculture, and trade openness being stationary at first difference [I(1)], while school enrolment is stationary at level [I(0)]. This combination of integration orders justifies the use of the ARDL–ECM framework. Optimal lag selection criteria predominantly favor a lag length of three, ensuring a well-specified dynamic structure.

The ARDL bounds test confirms the existence of a long-run cointegrating relationship among agricultural output, school enrolment, government expenditure on agriculture, and trade openness. Long-run estimates reveal that school enrolment and government expenditure on agriculture exert positive and statistically significant effects on agricultural output, underscoring the critical role of human capital development and sustained public investment in agriculture. In contrast, trade openness exhibits a negative but weakly significant effect, suggesting that increased openness has not translated into long-run gains in agricultural output, possibly due to structural and competitiveness constraints.

Short-run ECM results indicate that changes in government expenditure on agriculture positively influence agricultural output in the short term, although lagged expenditure effects are negative, reflecting adjustment dynamics and possible expenditure inefficiencies. Trade openness negatively affects agricultural output in the short run, reinforcing concerns about exposure to external competition and import dependence. The error correction term is negative and highly significant, confirming a stable long-run equilibrium and indicating that approximately 31% of short-run disequilibrium is corrected annually.

Goodness-of-fit statistics demonstrate strong explanatory power, with the model accounting for over 90% of variations in agricultural output. Diagnostic tests confirm the absence of serial correlation, heteroskedasticity, functional form misspecification, and non-normality, while CUSUM and CUSUMSQ tests indicate parameter stability over the sample period. Overall, the findings provide robust empirical evidence that human capital formation and government agricultural spending are central to enhancing agricultural output in Nigeria, while trade openness poses short- and long-run challenges to agricultural performance.

The overall robustness and stability of the model suggest that agriculture remains a viable anchor for Nigeria’s economic diversification strategy, provided it is supported by complementary investments in human capital and institutional capacity. Policymakers should adopt an integrated diversification framework that aligns education policy, agricultural investment, and trade strategy to reduce oil dependence and achieve sustainable economic transformation.

5.0 Conclusion and Recommendations

This study examined the role of human capital formation, government expenditure on agriculture, and trade openness in shaping agricultural output in Nigeria within an error correction framework. The findings confirm a stable long-run relationship among the variables, with school enrolment and government expenditure on agriculture exerting positive and statistically significant effects on agricultural output, underscoring the importance of education-driven productivity and sustained public investment for agricultural-led economic diversification. In contrast, trade openness was found to negatively affect agricultural output in both the short and long run, suggesting that structural constraints and weak competitiveness limit the capacity of Nigeria's agricultural sector to benefit from increased integration into global markets. The significant and negative error correction term further indicates that adjustments toward long-run equilibrium occur gradually over time.

Based on these findings, the study recommends that policymakers prioritize long-term investments in education and skills development tailored to agriculture, alongside improving the efficiency and targeting of public agricultural expenditures toward productivity-enhancing infrastructure, research, and extension services. Trade policy should be strategically managed to protect and strengthen domestic agricultural value chains while gradually enhancing competitiveness through export promotion and quality standards. A coherent and stable policy framework that integrates education, agricultural investment, and trade reforms is essential to harness agriculture as a sustainable driver of Nigeria's economic diversification and long-term growth.

REFERENCES

Adebayo, A. A., & Ojo, O. E. (2012). Human capital investment and agricultural productivity in Nigeria. Journal of Agricultural Economics and Development, 1(2), 28 – 34.

Adediran, O., & Omisakin, A. (2023). Human capital development and agricultural export performance in Sub-Saharan Africa. Journal of Development Policy Studies, 15(2), 112 – 130.

Adekunle, A., & Adebayo, O. (2020). Trade openness, human capital, and export diversification in Nigeria. African Economic Review, 8(1), 45 – 67.

Adeniyi, O., & Ogundipe, A. (2019). Human capital development and inclusive growth in Nigeria. Journal of Economic Policy Reform, 22(3), 1–18. https://doi.org/10.1080/17487870.2018.1432428

Adeyemi, S. L., & Ogunsola, A. J. (2016). Human capital development and economic growth in Nigeria. Journal of Economics and Sustainable Development, 7(12), 16–26.

Andy, K. J. (2019). Agricultural development and economic diversification in developing economies. African Journal of Economic Review, 7(2), 45–62.

Bakare, A. S. (2019). Economic diversification and sustainable growth in Nigeria. Journal of Economics and Development Studies, 7(1), 1–12.

Baron, R. M., & Kenny, D. A. (1986). The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. Journal of Personality and Social Psychology, 51(6), 1173 – 1182.

Becker, G. S. (1964). Human capital: A theoretical and empirical analysis, with special reference to education. University of Chicago Press.

Bello, A. A., Yusuf, A. A., & Lawal, W. A. (2021). Agricultural productivity and economic diversification in Nigeria. Journal of Agriculture and Food Economics, 9(1), 1–15. https://doi.org/10.1186/s40100-021-00185-4

Central Bank of Nigeria (CBN). (2023). Statistical Bulletin, Volume 34. Abuja: CBN.

Chindo, S., & Abdul-Rahim, A. S. (2018). Agricultural sector performance and economic growth in Nigeria. International Journal of Social Economics, 45(2), 273–287. https://doi.org/10.1108/IJSE-05-2016-0132

Danjuma, I., & Saidu, B. M. (2024). Human capital investment and agricultural output in Nigeria. Journal of African Development Studies, 16(1), 33–52.

FAO. (2021). Nigeria: Agriculture sector review. Food and Agriculture Organization of the United Nations.

Food and Agriculture Organization (FAO). (2022). FAO Statistical Yearbook. Rome: FAO.

Ijirshar, V. U. (2015). The empirical analysis of human capital development and agricultural growth in Nigeria. Journal of Economics and Sustainable Development, 6(2), 55–63.

International Trade Centre (ITC). (2023). Trade Map Database: Nigeria Export Profiles. Geneva: ITC.

Jaffee, S., & Masakure, O. (2005). Strategic use of private standards to enhance international competitiveness: Vegetable exports from Kenya and elsewhere. Food Policy, 30(3), 316–333. https://doi.org/10.1016/j.foodpol.2005.05.009

Lawal, J. O., Omonona, B. T., & Oluwatayo, I. B. (2019). Agricultural diversification and household welfare in Nigeria. Journal of Rural Economics and Development, 28(1), 1–18.

Lederman, D., Maloney, W. F., & Servén, L. (2010). Lessons from NAFTA for Latin America and the Caribbean. World Bank. https://doi.org/10.1596/978-0-8213-8317-5

Lucas, R. E. (1988). On the mechanics of economic development. Journal of Monetary Economics, 22(1), 3–42. https://doi.org/10.1016/0304-3932(88)90168-7

Matthew, A. O., & Adegboye, F. B. (2014). Agricultural output and economic growth in Nigeria: An econometric analysis. Journal of Economics and Sustainable Development, 5(2), 149–156.

National Bureau of Statistics (NBS). (2023). Annual Abstract of Statistics. Abuja: NBS.

Ogunjimi, J., & Adebayo, A. (2018). Agricultural output and economic diversification in Nigeria. Journal of Economics and Development Studies, 6(4), 75–86.

Okonkwo, I. V., & Edet, E. S. (2023). Trade openness, agricultural productivity, and economic diversification in Nigeria. African Development Review, 35(2), 245–260. https://doi.org/10.1111/1467-8268.12701

Okorie, C., & Agu, I. (2021). Agricultural output and non-oil export growth in Nigeria: An ARDL approach. Nigerian Journal of Economic Research, 27(1), 34–52.

Olawale, A. S., Adekunle, W., & Falade, O. (2022). Human capital and agricultural productivity in Nigeria. Journal of Economic Policy and Research, 17(2), 89–105.

Oluwatobi, S. O., & Ogunrinola, I. O. (2011). Government expenditure on human capital development: Implications for economic growth in Nigeria. Journal of Sustainable Development, 4(3), 72–80.

Oluwatobi, S., Adetayo, K., & Ojo, L. (2022). Agricultural productivity, human capital, and economic diversification in developing economies. Journal of African Economic Transformation, 6(3), 78–95.

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

Romer, P. M. (1990). Endogenous technological change. Journal of Political Economy, 98(5, Part 2), S71–S102. https://doi.org/10.1086/261725

Sala-i-Martin, X., & Subramanian, A. (2013). Addressing the natural resource curse: An illustration from Nigeria. Journal of African Economies, 22(4), 570–615. https://doi.org/10.1093/jae/ejs033

Schultz, T. W. (1961). Investment in human capital. The American Economic Review, 51(1), 1–17.

Udeh, S. N., & Nwakuya, M. T. (2020). Human capital development and agricultural growth in Nigeria. International Journal of Agricultural Economics, 5(3), 45–55. https://doi.org/10.11648/j.ijae.20200503.11

UNIDO. (2019). Industrial development report 2019: Demand for manufacturing. United Nations Industrial Development Organization.

Van der Ploeg, F. (2011). Natural resources: Curse or blessing? Journal of Economic Literature, 49(2), 366–420. https://doi.org/10.1257/jel.49.2.366

World Bank (2023). World Development Indicators (WDI). Washington, DC: World Bank.

World Trade Organization (2023). Trade Policy Review: Nigeria. Geneva: WTO.