INTERNATIONAL JOURNAL OF RESEARCH AND INNOVATION IN SOCIAL SCIENCE (IJRISS)
ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume IX Issue XV September 2025 | Special Issue on Economics

Dynamic Interaction Between Demand and Supply Shocks in Agricultural Output: Evidence from Nigeria

Lois Ore Oyiza NYAMIDA

Department of Economics, Federal College of Education Okene, Nigeria

Department of Economics and Development Studies, Kwara State University Malete, Nigeria

DOI: https://dx.doi.org/10.47772/IJRISS.2025.915EC0074

Received: 02 September 2025; Accepted: 08 September 2025; Published: 09 October 2025

ABSTRACT

This study investigates the dynamic interaction between demand-side and supply-side shocks in determining agricultural output in Nigeria from 1981 to 2023. Despite agriculture's critical role in the Nigerian economy, its output continues to fall short of meeting the nation's growing demand. This study adopts a Structural Vector Autoregression (SVAR) model to examine how shocks originating from exchange rate fluctuations, climate variability, and security conditions and inflation affect agricultural output over time. Using annual time series data, the findings revealed that agricultural output in Nigeria is influenced by both demand and supply shocks, with climate and inflation exerting the most persistent effects. Results from impulse response functions (IRFs) and forecast error variance decomposition (FEVD) revealed that agricultural output is highly sensitive to climate shocks and inflation. Temperature and inflation shocks exert the most significant and persistent negative effects on output, while security and exchange rate shocks have relatively moderate but notable impacts. The findings highlight Nigeria's agricultural vulnerability to macroeconomic instability and environmental volatility, particularly in the context of rising food insecurity and climate change. Additionally, supply shocks, especially from temperature changes, exert stronger short-term effects than demand shocks. These results imply that policy efforts aimed at stabilising food production must be multidimensional addressing climatic vulnerability, insecurity, and macroeconomic instability simultaneously. The study recommends investments in climate-smart agriculture, inflation-targeting frameworks, and active involvement of stakeholders in promoting resilience measures that are directly responsive to farmers' practical challenges.

Keywords: Agricultural output, climate variability, demand-side shocks, supply-side shocks, SVAR

INTRODUCTION

Agriculture remains a cornerstone of the Nigerian economy, contributing approximately 23% to GDP and employing a significant proportion of the workforce (World Bank, World Development Indicators [WDI], 2024; Salisu & Alamu, 2023). Historically, Nigeria was a global leader in the production of numerous agricultural commodities (Olalekan, 2019). But over time, agricultural output in Nigeria has failed to match the increasing demand driven by population growth, urbanization and rising incomes, leading to increased food imports and worsening food insecurity (Aina et al., 2019; OECD, 2016). The sector's performance has weakened due to multiple internal and external shocks which include; economic instability, policy inconsistencies, climate risks, population pressures, and rising insecurity, all of which have constrained the sector's ability to meet the rising domestic food demand (Ewubare & Iyabode, 2020; Gavrilova, 2021; Nyamida, 2023).

Recent statistics project that nearly 31.8 million Nigerians will face acute food insecurity in 2024, up from 24.9 million in 2023 (Food and Agriculture Organization [FAO], 2024). This raises critical questions about the structural resilience of Nigeria's agricultural system and its responsiveness to both market and environmental shocks. According to Assouto et al. (2020) yield risk affects farmers' decision-making, as they must consider the potential for both yield fluctuations and price volatility. This interplay influences overall agricultural output and the availability of food, making it a key factor in the stability of the agricultural sector and national food security (Boussard, 2010; Sadoulet & De'Janvry, 1995 in Assouto et al., 2020; Serra, 2015). The inability of farmers to meet demand is, among other things, attributed to the weak supply response of smallholders who do not systematically respond to market signals (Di'Marcantonio et al., 2014; Magrini et al., 2017). According to Bordirsky (2015); Deann (2021); Sonmez, (ND) demand factors, such as population shifts and per capita income, as well as supply chain crunches, labour shortages, raw material shortages, and transportation issues can also affect agricultural output. Sub-Saharan African countries have continued to struggle to meet demand due to population growth and urbanization pressures (Organisation of Economics in Cooperative Development [OECD], 2016).

Understanding how shocks from both demand and supply sides interact to shape agricultural output trends over time in Nigeria is crucial for policymakers, researchers and development practitioners. In the context of government's renewed push for economic diversification and food self-sufficiency, in the midst of an increasingly volatile economic and climatic environment, this research offers a timely evaluation of Nigeria's agricultural vulnerabilities, understanding the dynamic interplay between demand-side and supply-side shocks. This interaction is critical to understanding output volatility and designing effective interventions.

Therefore, this study is undertaken to explore the dynamic interaction between demand-side and supply-side shocks and their impact on agricultural output. This study is novel in the sense that it focuses on the dynamic interaction between demand-side and supply-side shocks and their impact on agricultural output in Nigeria, which is an area that has received less attention in previous empirical studies as most studies (Gershon & Mbajekwe, 2020; Henry, 2022; Toriola, 2022) assessed specific determinants of agricultural output in isolation.

Furthermore, by employing a Structural Vector Autoregression (SVAR) approach, it provides new evidence on how shocks interact jointly to shape agricultural performance over time. By doing so, the study covers the period of 43 years (1981 to 2023), capturing major economic policy shifts, demographic trends, climate variability, and external shocks. Thus, providing valuable insights for policymakers and implementers on how to build a more shock-resilient agricultural sector. The rest of the paper presents reviews of relevant literatures and theories, methodology, analysis and discussion of results, conclusion and policy recommendation.

LITERATURE REVIEW

Theoretical Review

Neoclassical Growth Theory

The Neoclassical Growth Theory, developed by Solow and Swan (1956), remains foundational to modern growth analysis. It posits that long-run output is determined by capital, labour, land, and exogenous technological progress, formalized through a production function with constant returns to scale and diminishing returns to individual factors. Technological progress operates as the ultimate driver of sustained growth, while capital and labour explain transitional dynamics. Refinements by Cass and Koopmans (1965) strengthened the microfoundations by linking savings and investment decisions to intertemporal optimization, though technological progress remained exogenous. The strength of this framework lies in its elegant separation of input accumulation and technological progress, which allows researchers to distinguish between factor-driven growth and productivity-driven growth. However, it faces notable limitations: the assumptions of perfect competition, full employment, and exogenous technology are rarely realistic in developing agricultural economies. Moreover, it has limited capacity to explain short-run fluctuations in output, which are often driven by shocks beyond factor accumulation.

For the present study, the Neoclassical Growth Theory provides a benchmark for understanding Nigeria's agricultural potential, grounded in factor endowments and productivity. Yet its shortcomings in capturing short-term volatility justify extending the analysis to frameworks that explicitly account for exogenous shocks and structural rigidities.

Real Business Cycle (RBC) Theory

Emerging from the work of Kydland and Prescott (1982), Real Business Cycle Theory transformed macroeconomic thought by attributing cyclical fluctuations to real shocks, particularly technology shocks rather than to monetary disturbances or rigidities. Its core propositions rest on rational expectations, market clearing, and price flexibility, with agents optimizing behaviour in response to shocks. Methodologically, it introduced Dynamic Stochastic General Equilibrium (DSGE) models and advanced the empirical use of Vector Autoregressions (VAR), particularly Structural VARs (Sims, 1980), to identify and trace the effects of shocks through impulse response functions and variance decompositions. The strength of this theory lies in its rigorous micro foundations and its integration of growth and cycle analysis into a unified framework. It provides powerful tools for identifying structural shocks and modelling their propagation through the economy. However, the framework is often criticised for assuming perfectly flexible markets and ignoring institutional frictions assumptions that are challenging issues in Nigeria, where markets are fragmented and agricultural production is subject to structural bottlenecks.

For this study, RBC theory contributes the methodological justification for adopting a Structural VAR approach to analyse agricultural output. It supports the treatment of temperature, security, exchange rate, and inflation as identifiable structural shocks, allowing their dynamic effects on agricultural output to be empirically traced and evaluated.

Structuralist School of Development Economics

The Structuralist School, rooted in the mid-twentieth-century work of Rosenstein-Rodan, Nurkse, and Hirschman, and later formalized by Lance Taylor (1991), emphasises the distinctive features of developing economies. It argues that structural rigidities such as supply inelasticities, dependence on primary commodities, foreign exchange constraints, and weak institutions shape economic outcomes and amplify vulnerability to external shocks. For agriculture, these features include dependence on rain-fed production, limited mechanization, and reliance on imported inputs such as fertilizers and machinery. The strength of the Structuralist approach lies in its realistic account of the institutional and structural frictions that other theories tend to ignore. It explains why shocks often have outsized effects in developing economies and why policy responses may be constrained. Its limitation, however, is the absence of formalised framework and predictive precision compared to neoclassical or RBC frameworks. For the Nigerian agricultural sector, the structuralist perspective explains why shocks such as exchange rate volatility, inflation, and security disruptions exert disproportionate impacts on output. By embedding the analysis in the realities of institutional weakness and external dependence, the structuralist view complements the more abstract assumptions of neoclassical and RBC theories.

Empirical Literature Review

Barros et al. (2009) investigated the relative importance of supply and demand shocks in explaining the growth trajectory of Brazilian agriculture over a period spanning 1967 to 2003. Their study employed a Structural Vector Autoregression (SVAR) model, estimated using annual data on agricultural output, yield (productivity), real exchange rate, domestic GDP, and agricultural prices. Drawing from the framework of Blanchard and Quah (1989), but applying Bernanke's identification strategy, the authors were able to disentangle the structural shocks driving agricultural performance. Their findings revealed that supply-side shocks, particularly those linked to yield improvements, were the dominant drivers of agricultural output growth, explaining over 50% of the forecast error variance in output. In contrast, demand-side factors, such as GDP and exchange rate movements, accounted for approximately 10% and 16% of output variation respectively. Though to a lesser extent, but still meaningfully. Notably, while yield improvements had a strong positive effect on output, their effect on prices was moderate, suggesting that technological progress did not undermine farm incomes through price suppression. This was attributed to Brazil's increasing integration with international markets, which absorbed surplus production and maintained profitability. The authors argue that Brazil's ability to leverage external demand was key to supporting the adoption of yield-improving technologies and sustaining long-term agricultural growth. The study highlights the critical role of investment in agricultural research and technology in sustaining output growth. It also underscores the importance of maintaining open trade policies and favourable exchange rate regimes, particularly given the inelastic nature of domestic food demand.

Nimo (2012) examined agricultural productivity and supply responses in Ghana. Using the duality modeling technique and data from the Ghana Living Standard Survey (GLSS4), the study examined Agricultural Supply Response (ASR) across different regions and crop types while considering technical inefficiencies that affect production. Key findings revealed significant inefficiencies, with a national average of 53% and regional variations, such as higher inefficiency among groundnut farmers in the Coastal zone (83%) and lower inefficiency among cowpea farmers in the Savannah zone (30%). The research indicated that farmers are responsive to both price and non-price factors, but responses are lower when accounting for production inefficiencies, suggesting potential overestimation in past studies. It also identified non-price factors like plot size, animal capital, labour, and education as crucial for policy development. The study concluded that addressing technical inefficiencies and adopting region-specific policies could enhance agricultural output and competitiveness in Ghana. Thus, addressing high inefficiencies in agricultural production calls for targeted policies to improve technical efficiency and implement region-specific solutions. It is also implied by the study that strengthening non-price factors like plot size, labour, and education is essential for increasing productivity.

Oruonye et al. (2020) examined the impact of farmer–herder conflict on food security in Nigeria, using Taraba State as a case study. The study aimed to explore how rising violence between pastoralists and crop farmers affects local agricultural productivity and household food access. Utilizing structured questionnaires and descriptive statistical analysis, the authors gathered data from affected communities to understand both the causes and consequences of the conflict. The findings revealed that the conflict has escalated in scale and lethality, with the increasing use of firearms including AK-47s, driven by land tenure disputes, encroachment on grazing routes, ethnic and religious tensions, and the collapse of traditional mediation systems. Crucially, the study found that these persistent conflicts significantly disrupt food production, displace households, and result in widespread asset losses, thereby worsening food insecurity in already vulnerable rural areas. The findings implies that resolving farmer–herder conflict is not only a security imperative but also a necessary condition for restoring agricultural output and ensuring sustainable food systems. The authors underscore the urgent need for comprehensive land reform, conflict resolution mechanisms, and inclusive policy frameworks that address both the socio-economic and security dimensions of the crisis.

Gershon and Mbajekwe (2020) examined the relationship between climate change and agricultural production (crop and livestock) in Nigeria using time series data from 1981-2017. Variables used to depict climate change are mean annual rainfall, temperature and carbon dioxide emissions. Data on crop yield was collated for 17 major crops produced in Nigeria with the livestock production index of Nigeria. Econometric analysis was carried out using autoregressive distributed lag (ARDL). The results showed that there is a long run relationship between climate change and crop production while no long run relationship exists between climate change and livestock production. Furthermore, evidence is provided that rainfall and CO_2 emissions have a positive and significant effect on crop yield in the long run while temperature has a negative and significant effect on crop yield in the long run. It also was seen that four period lagged rainfall has a positive and significant effect on livestock production; two period lagged temperature had a negative significant effect and one period lagged CO_2 emissions had a negative significant effect on livestock production in Nigeria.

Ketema (2020) investigated the determinants of agricultural output in Ethiopia between 1980 and 2018 using the ARDL approach. The result revealed that fertilizer and input import in the short run and long run affect agricultural output positively and significantly. On the other hand drought had a significantly negative effect both in the short run and long run. Whereas, rainfall, trade openness, inflation rate, affect agricultural output positively and significantly in the longrun. In the short run labour force affects positively and significantly while rainfall affects positively and insignificant. This study emphasises the need to ensure a consistent and affordable supply of inputs to support agricultural output growth, while investments in irrigation and drought-resistant crops could help mitigate climate-related challenges.

Ewubare and Iyabode (2020) conducted a study on the impact of agricultural production determinants on agricultural output in Nigeria. The OLS results after unit root test was conducted using granger causality test statistics showed that agricultural funding, agricultural credit/loan as well as exchange rate have positive relationship with agricultural production output. Also, the granger causality test shows that agricultural funding, agricultural credit loan as well as exchange rate impact on agricultural production output. The study highlights the importance of financial instruments such as agricultural loans and exchange rate stability in driving agricultural production, supporting the view that access to credit and favourable financial conditions are essential.

Ogunjimi (2020) examined the impact of exchange rate fluctuations on the performance of Nigeria's agricultural, industrial, and services sectors, employing both symmetric and asymmetric models. Using annual time-series data from 1981 to 2016, obtained from the Central Bank of Nigeria (CBN), the analysis was carried out using the Auto-Regressive Distributed Lag (ARDL) and Nonlinear ARDL (NARDL) frameworks. Findings from the linear ARDL model suggested that exchange rate variations positively influence the performance of the agricultural and services sectors in the short run. Similarly, results from the nonlinear ARDL model indicated that both appreciation and depreciation of the exchange rate are positively associated with agricultural and services sector output but exert a negative influence on the industrial sector. However, the study finds no evidence of asymmetric effects of exchange rate movements on sectoral output, implying that exchange rate appreciation and depreciation have symmetric impacts on all sectors, both in the short and long run.

Similarly, Awolaja and Okedina (2020) investigated the impact of both real exchange rate appreciation and depreciation on Nigeria's aggregate and sub-sectoral agricultural output. Employing a nonlinear Auto-Regressive Distributed Lag (NARDL) cointegration approach, the study explored both short run and long run asymmetric relationships between the real exchange rate and agricultural productivity. The results revealed a long run cointegrating relationship between the variables. Specifically, real exchange rate appreciation was found to exert a significant positive effect on agricultural output, while depreciation had a significant negative impact. Furthermore, the positive influence of exchange rate appreciation on agricultural output was more pronounced than the adverse effect of depreciation. These findings highlight the importance of implementing a carefully managed exchange rate policy to support and enhance agricultural sector performance.

The study of Toriola (2022) examined the effect of commodity prices on agricultural output in Nigeria. In the empirical model, agricultural output depends on maize, wheat, soya beans, and oil prices. Data covering 1991 and 2017 from the Central Bank of Nigeria Statistical Bulletin and Food and Agricultural Organisation database was analysed using a Fully Modified OLS (FMOLS) technique. The result shows that maize and soya bean prices positively affect agricultural output, while wheat prices and oil prices negatively affect agricultural output in Nigeria. This implies that agricultural output increases with increased agricultural commodity prices and falls with an increase in oil prices. The findings suggest that agricultural output in Nigeria is highly sensitive to global commodity prices, and oil price volatility could undermine agricultural growth.

Henry et al. (2022) studied on the determinants of agribusiness output in Nigeria from 1981 to 2018. The determinants of agribusiness output selected for the study were categorised into climatic (annual rainfall and temperature) and non-climatic factors (farm size, exchange rate, inflation rate, monetary policy rate, capital and labour employed in agribusiness). Results from the ARDL bounds test indicated that there was long-run relationship between agribusiness output and its observed determinants. The long-run estimates revealed that agribusiness output was majorly determined by temperature level, exchange rate, capital and labour employed. On the other hand, the short-run estimates indicated that all both climatic and non-climatic factors were significant determinants of agribusiness output in Nigeria. Thus, emphasising the importance of both climatic and non-climatic factors in driving agribusiness output, with implications for policy related to climate adaptation and business development in agriculture.

Ngobeni and Muchopa (2022) examined the effects of government expenditure in agriculture, annual average rainfall, consumer price index, food import value, and population on the value of agricultural production with a specific focus on government expenditure in agriculture for the period 1983 to 2019 in South Africa. Using the Johansen cointegration test, the results revealed that there is a long-run relationship among the variables. The Granger causality test results suggested that government expenditure in agriculture does not Granger cause the value of agricultural production. However, the two variables are linked through other variables in the model, such that an increase in government expenditure in agriculture, average annual rainfall, and population were

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume IX Issue XV September 2025 | Special Issue on Economics

shown to ultimately increase the value of agricultural production based on vector autoregressive (VAR) model analysis. In contrast, an increase in the consumer price index and food import value was seen to be detrimental to the value of agricultural production. This study suggests that Government expenditure should focus on infrastructure and production-boosting initiatives, with a strong emphasis on managing inflation and food imports to protect the agricultural sector's value.

The reviewed empirical studies underscore the diverse and dynamic factors influencing agricultural output across different contexts. Barros et al. (2009) identified supply-side shocks, particularly yield improvements, as the primary drivers of Brazil's agricultural growth, with demand-side factors playing secondary roles. Nimo (2012) found that technical inefficiencies significantly reduce supply responsiveness in Ghana, suggesting the need for efficiency-focused policies. Studies by Gershon and Mbajekwe (2020) in Nigeria and Ketema (2020) in Ethiopia, show that climate variables and input availability have both short and long run effects on output, while access to credit and exchange rate dynamics (Ewubare & Iyabode, 2020; Ogunjimi, 2020; Awolaja & Okedina, 2020) were also found to influence productivity. Other studies highlight the importance of commodity prices (Toriola, 2022), agribusiness factors (Henry et al., 2022) and public spending (Ngobeni & Muchopa, 2022). Despite these rich findings, most studies are either country-specific or limited to short-term relationships and sectoral variables; less attention has been given to examine how these factors interact dynamically. Therefore, this study seeks to bridge this gap by exploring the dynamic interaction between demand-side and supply-side shocks and their impact on agricultural output.

METHODOLOGY

Theoretical Framework

This study is anchored on the Real Business Cycle (RBC) Theory, which views output fluctuations as the economy's response to real shocks such as climate variability, security disruptions, and macroeconomic volatility. These shocks transmit through production and demand channels, creating short-run deviations in output. The RBC framework is particularly relevant because it connects directly to modern empirical tools like Structural Vector Autoregressions (SVARs), which allow for the identification of structural shocks and the analysis of their dynamic effects. This makes it a suitable foundation for examining the interaction of supply and demand shocks in Nigeria's agricultural sector.

Complementing this, the Neoclassical Growth Theory establishes the benchmark of long-run output potential, while the Structuralist School of Development Economics contextualises the Nigerian case by highlighting structural rigidities such as weak institutions, rain-fed agriculture, and external vulnerabilities. Together, these perspectives clarify the distinction between long-run growth and short-run fluctuations, while also grounding the analysis in the specific realities of a developing economy. On this basis, the study adopts an SVAR framework to capture the dynamic effects of supply shocks and demand-side shocks on agricultural output in Nigeria.

Model Specification

Building on this theoretical foundation, the empirical strategy employs a Structural Vector Autoregression (SVAR**)** model to capture the dynamic interactions between agricultural output and the identified shocks. In specifying the SVAR model, a combination of log-transformed and level variables was employed. Logarithmic transformation was applied to variables measured in monetary units (exchange rate), to allow interpretation of coefficients and shocks in percentage terms. Variables measured as rates or with zero/negative values (temperature, security and inflation) were retained in levels. This approach maintains both interpretability and adherence to statistical assumptions regarding integration order and stationarity.

The SVAR model is represented as:

$$\mathrm{AY_t = Bu_t} \qquad (1)$$

Where $\mathrm{Y_t}$= a vector of endogenous variables.

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume IX Issue XV September 2025 | Special Issue on Economics

$$Y_t = [Temp_t, Secr_t, \ln(Exr_t), Infl_t, Agopt_t,]' \qquad (2)$$

$Temp_t$, $Secr_t$, $lnExr_t$, $Infl_t$, $Agopt_t$ = temperature, security, log of exchange rate, inflation and agricultural output.

A = the matrix capturing contemporaneous relationships between the endogenous variables.

B= the matrix that identifies the structural shocks.

u_t = a vector of orthogonal structural shocks representing innovations in each variable.

Data Description, Source and Measurement

The study used an annual data spanning from 1981 to 2023. Data on Agricultural output, proxied by agriculture value added, measured as a percentage of GDP was sourced from World Bank WDI database. Inflation is captured as the annual percentage change in consumer prices and sourced from World Bank WDI database. Exchange rate, represented by the nominal bilateral exchange rate (measured as local currency units per US dollar, period average) and was sourced from World Bank WDI database. Data on temperature (measured in degrees celsius) was sourced from the World Bank Climate Change Knowledge Portal. Security proxied by government expenditure on internal security as % of GDP was sourced from CBN Statistical Bulletin.

Estimation Technique

A Structural Vector Autoregression (SVAR) model is employed to capture the interaction between structural demand and supply shocks in determining agricultural output. The SVAR model includes five endogenous variables: temperature security, exchange rate, inflation and agricultural output. Each variable is associated with a specific type of structural shock. Temperature represents climate shocks, which are assumed to be exogenous and affect all other variables contemporaneously. Security captures internal shocks stemming from domestic instability or conflict. The exchange rate reflects external sector shocks, driven by international factors such as capital flows or trade conditions. Inflation embodies price or uncertainty shocks, typically affecting input costs and market expectations. Agricultural output serves as the endogenous response variable, influenced by both demand and supply-side shocks. The SVAR identification follows a recursive short-run restriction imposed on the A matrix using the Cholesky decomposition, assuming that temperature (climate shock) is the most exogenous, while agricultural output is the most endogenous. Additionally, the B matrix is assumed to be diagonal, implying that each structural shock directly affects only its corresponding endogenous variable contemporaneously. This specification enables the analysis of the short and medium-term transmission of shocks within the agricultural sector and supports the investigation of joint dynamics between the demand and supply sides of the economy.

The identification scheme for A matrix and B matrix are presented below:

Structural A Matrix

The SVAR model imposes **recursive (Cholesky-type) restrictions** on the A matrix, assuming a lower-triangular form where each variable may be contemporaneously affected by those ordered before it, but not by those after. The matrix form is presented below:

$$A = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ a_{21} & 1 & 0 & 0 & 0 \\ a_{31} & a_{32} & 1 & 0 & 0 \\ a_{41} & a_{42} & a_{43} & 1 & 0 \\ a_{51} & a_{52} & a_{53} & a_{54} & 1 \end{bmatrix}$$

This implies that agricultural output is contemporaneously influenced by all four preceding variables, while temperature is purely exogenous in the same period.

Structural B Matrix

The B matrix represents the immediate response of each variable to its own structural shock. The B matrix is diagonal, implying that each variable responds only to its own contemporaneous structural shock, and the innovations are uncorrelated:

$$B = \begin{bmatrix} b_{11} & 0 & 0 & 0 & 0 \\ 0 & b_{22} & 0 & 0 & 0 \\ 0 & 0 & b_{33} & 0 & 0 \\ 0 & 0 & 0 & b_{44} & 0 \\ 0 & 0 & 0 & 0 & b_{55} \end{bmatrix}$$

This assumption ensures that each identified shock can be interpreted independently of the others. It also guarantees that the structural shocks have unit variance and no contemporaneous correlation, as required for orthogonality.

Through the use of impulse response functions (IRFs) and forecast error variance decomposition (FEVD), the SVAR model provides dynamic insights into how agricultural output adjusts over time to innovations in both demand and supply conditions. This makes it a valuable tool for evaluating the temporal and interactive effects of economic shocks on the agricultural sector.

DISCUSSION OF FINDINGS

Descriptive Analysis

Table 1: Descriptive Statistics of the Variables

Variables	Observations	Mean	Median	Maximum	Minimum	Std. Dev.
AGOPT	43	22.89659	22.72494	36.96508	12.24041	4.480943
TEMP	43	27.25163	27.31000	27.92000	26.36000	0.328125
SECR	43	0.438341	0.409253	0.946949	0.169666	0.149015
LNEXR	43	3.712427	4.775475	6.111038	-0.481739	2.450485
INFL	43	19.07948	13.00697	72.83550	5.388008	16.28122

Note: AGOPT, TEMP, SECR, lnEXR and INFL, represent the Agricultural output, temperature, security natural log of exchange rate and inflation respectively.

Source: Author’s computation 2025, using E-views

Table 1 presents a descriptive summary of the key variables used in the study, based on 43 annual observations from 1981 to 2023. The focus is on central tendency (mean and median), dispersion (standard deviation), and the range (minimum and maximum), offering insights into the data distribution and variability over time. Agricultural output (AGOPT), measured as the share of agriculture in GDP, has an average value of 22.90%, with a median of 22.72%. The minimum and maximum values are 12.24% and 36.97% respectively, suggesting moderate variation across the years, as further evidenced by a standard deviation of 4.48. This reflects relatively stable agricultural contribution to GDP, though with some fluctuations. Temperature (TEMP) displays remarkable stability across the study period. The mean temperature is 27.25°C, with a narrow range between 26.36°C (minimum) and 27.92°C (maximum). The standard deviation is only 0.33°C, indicating minimal fluctuation. While temperature changes may seem negligible year-to-year, even small shifts can have cumulative or spatially varied impacts on agricultural output.

Security expenditure (SECR), expressed as a percentage of GDP, shows a low mean of 0.44% and a small standard deviation (0.15), but the range (0.17% to 0.95%) reflects gradual increases likely associated with rising internal security challenges. Log of exchange rate (LNEXR) is approximately 3.71, the median (4.78) is noticeably higher than the mean, suggesting a left-skewed distribution, The maximum LNEXR value (6.11) reflects periods of sharp exchange rate depreciation due to macroeconomic instability or policy devaluations, while the minimum value (-0.48) suggests a stronger currency phase, likely under earlier fixed or overvalued exchange rate regimes. The standard deviation is 2.45, reflecting a relatively high level of volatility in the exchange rate over the period. This high dispersion underscores the unstable and often unpredictable nature of Nigeria's exchange rate system during the era under review, which shifted between fixed, managed float, and flexible regimes.

Lastly, Inflation rate (INFL), measured as the annual percentage change in the Consumer Price Index (CPI), also exhibits considerable variation. The average inflation rate is 19.08%, with a median of 13.01%, a maximum of 72.84%, and a minimum of 5.39%. The relatively high standard deviation of 16.28% suggests that inflation has been inconsistent, with notable spikes likely tied to periods of economic crisis, fiscal imbalances, or supply shocks. The gap between the mean and median implies that the distribution of inflation is positively skewed due to a few extreme values.

Unit Root Test

In testing for the stationarity of variables, the Augmented Dickey-Fuller (ADF) unit root test was carried out. This test was necessary to avoid spurious regression which is often associated with non-stationary series. The result of the Augmented Dickey-Fuller (ADF) unit root test is presented in Table 2.

Table 2: Unit Root Test Result

Variables	ADF Statistics	Critical Value (5%)	P-Value	Order of Integration
AGOPT	-5.919257	-5.175710	< 0.01	I(0)
TEMP	-5.990396	-5.175710	< 0.01	I(0)
SECR	-6.138887	-5.175710	< 0.01	I(0)
LNEXR	-9.720634	-5.175710	< 0.01	I(0)
INFL	-5.786960	-5.175710	< 0.01	I(0)

Note: AGOPT, TEMP, SECR, lnEXR and INFL, represent the Agricultural output, temperature, security natural log of exchange rate and inflation respectively.

Source: Author's Computation 2025, using Eviews

The result on table 2 shows that all variables are integrated at level (I(0)). This confirms that the Structural Vector Autoregression (SVAR) model estimation is appropriate.

Lag Length Selection Criteria

In order to estimate structural vector autoregressive model specified in chapter 3, it is needful to determine the optimal lag length to be used. The optimal lag length for the VAR model was determined using standard information criteria, including the Akaike Information Criterion (AIC), Hannan-Quinn (HQ), Schwarz Criterion (SC), Final Prediction Error (FPE), and the Likelihood Ratio (LR) test. The lag selection criteria result is presented in table 3.

Table 3: VAR Lag Selection Criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-314.8295	NA	6.062609	15.99147	16.20258	16.06780
1	-202.1562	191.5446	0.076522	11.60781	12.87447*	12.06579
2	-172.3289	43.24953	0.063909	11.36644	13.68865	12.20608
3	-134.8937	44.92219*	0.040429*	10.74469*	14.12245	11.96598*

Note: * indicates lag order selected by the criterion; LR, FPE, AIC, SIC and HQ indicate sequential modified LR test statistic, Final Prediction Error, Akaike Information Criterion, Schwartz Information Criterion and Hannan-Quinn respectively

Source: Author's computation 2025, using Eviews

From table 3, SC suggested a lag length of one, while the FPE, AIC, HQ, and LR criteria indicated a lag length of three. Given the dominance of these criteria and the need to adequately capture dynamic relationships among the variables, a lag length of three was selected for the SVAR estimation to ensure comprehensive capture of the short run dynamics among the selected macroeconomic and environmental variables.

Given the mixed outcomes from the lag selection criteria, the AR root test was used to confirm the stability of lag length criterion recommended. It is worth noting that the AR root stability test and the eigenvalue stability condition are equivalent approaches, since both assess whether the system's characteristic roots/eigenvalues lie inside the unit circle. The AR root test was adopted here as the graphical method of confirmation. Figure 1 presents the AR root stability test result of the model at lag 3.

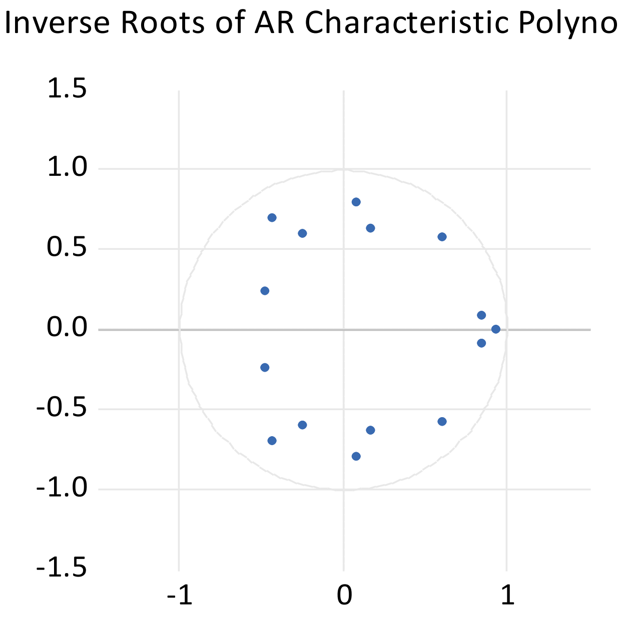


Figure 1: Stability Condition Result

Source: Author's computation 2025, using Eviews

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume IX Issue XV September 2025 | Special Issue on Economics

Figure 1 shows that all roots lie within the unit circle, as the modulus of each complex root is less than one. This indicates that the SVAR model estimated with a lag length of three satisfies the necessary stability condition.

Structural Vector Autoregression (SVAR) Model Estimation Analysis

The contemporaneous structure was identified using a recursive (Cholesky) decomposition, with variable ordering informed by economic theory. While structural coefficients were estimated, the focus of the analysis centers on impulse responses and forecast error variance decomposition.

Impulse Response Function (IRF) Analysis

Impulse response functions were used to trace the effect of one standard deviation structural shocks on the endogenous variables over a 10 year horizon. Figure 2 displays the IRFs showing how agricultural output responds to each structural shock.

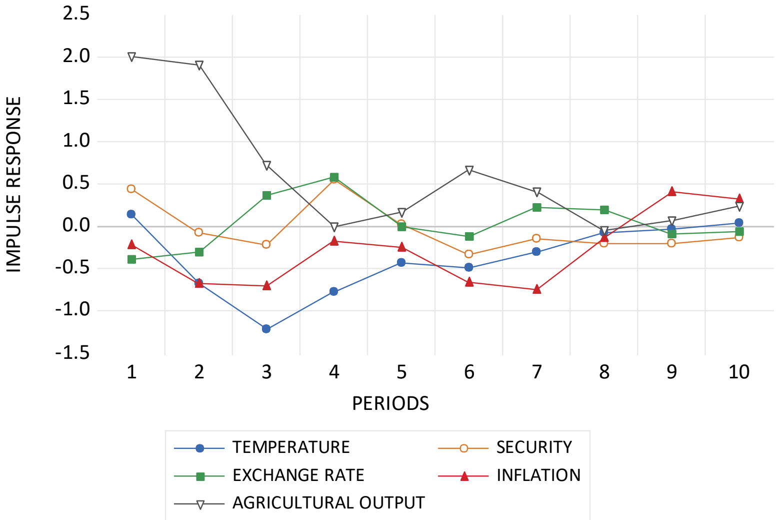


Figure 2: IRF of Agricultural Output to Structural Shock

Source: Author's computation 2025, using Eviews

The Impulse Response Function (IRF) analysis derived from the Structural Vector Autoregression (SVAR) model provides critical insights into the dynamic effects of structural shocks to temperature, security, exchange rate, and inflation on agricultural output, measured as a percentage of GDP. The IRFs trace the impact of each shock over a 10-period horizon, highlighting how agricultural output responds over time to innovations in the key explanatory variables.

A structural shock to temperature induces an immediate negative effect on agricultural output, with the strongest impact observed in the early periods, particularly around period three. Although the sector shows signs of gradual recovery in subsequent periods, the adjustment is relatively slow, implying that climatic shocks such as extreme weather events or unseasonal variations disrupt agricultural production and reduce its contribution to GDP in the short run. This underscores the vulnerability of agriculture to climatic shocks, consistent with Gershon and Mbajekwe (2020); McArthur and McCord (2017).

The response to a security shock follows a similar pattern but is more persistent. Agricultural output declines in the early periods and remains below its baseline level across much of the 10 period horizon. This sustained impact highlights how insecurity through displacement, restricted access to farmlands, and damaged infrastructure can impose lasting constraints on agricultural productivity and economic contribution (Oruonye et al. 2020).

In contrast, a shock to the exchange rate results in a short-term improvement in agricultural output, with a peak response occurring within the first two periods. This may reflect gains from improved competitiveness of local agricultural products in response to currency depreciation. This finding is consistent with Ogunjimi (2020). However, the effect is not stable, as output becomes volatile in the medium term, likely due to rising input costs from imported agricultural goods that offset initial benefits. This supports Awolaja and Okedina (2020) and Odey et al. (2023), who concluded that prolonged depreciation negatively affects agricultural output by raising production costs.

The IRF also shows that inflation shocks produce the most prolonged and consistently negative effects on agricultural output. The decline begins immediately after the shock and persists over several periods, underscoring how inflation erodes input affordability, reduces real incomes, and discourages investment in the agricultural sector, corroborating Aye and Odhiambo (2021).

Finally, a shock originating from agricultural output itself leads to a sharp and immediate decline in its GDP share. Although partial recovery occurs over time, the response remains unstable, indicating that the sector lacks strong internal stabilisers and is highly sensitive to self-reinforcing disruptions.

These findings demonstrate that agricultural output in Nigeria is particularly vulnerable to macroeconomic instability and environmental stress. Shocks to inflation and temperature exert the most harmful effects, while improvements in security and more stable exchange rate regimes could help buffer agricultural performance. Overall, these findings call for policies that enhance climate resilience, stabilise prices, and promote structural improvements in agriculture to buffer the sector against adverse shocks.

Forecast Error Variance Decomposition (FEVD) Analysis

Variance decomposition was conducted to evaluate the relative contribution of each shock to forecast errors in agricultural output over time.

Table 4 offers further insight into the dynamic interrelationships influencing agricultural output (AGOPT) by quantifying the proportion of its forecast error variance that can be attributed to shocks in its own past values and those of other macroeconomic and environmental variables namely temperature (TEMP), security (SECR), exchange rate (LNEXR), and inflation (INFL) over a ten period forecast horizon.

Table 4: Forecast Error Variance Decomposition (FEVD) Result of Agricultural Output

Period	S.E.	TEMP	SECR	LNEXR	INFL	AGOPT
1	2.103681	0.431864	4.485917	3.358170	0.957228	90.76682
2	3.011814	5.107997	2.250857	2.645286	5.401697	84.59416
3	3.427311	16.47512	2.141573	3.254393	8.322112	69.80680
4	3.608475	19.42300	4.263365	5.620616	7.719536	62.97348
5	3.644617	20.37827	4.189338	5.509720	7.980401	61.94227
6	3.811760	20.26448	4.553798	5.114962	10.28164	59.78511
7	3.926362	19.67709	4.410852	5.175154	13.28449	57.45241
8	3.938624	19.58069	4.624222	5.388370	13.30198	57.10473
9	3.967399	19.30206	4.815128	5.349552	14.21968	56.31358
10	3.990833	19.08666	4.858021	5.304737	14.73179	56.01879

Note: S.E, TEMP, SECR, EXR, INFL, AGOPT indicate standard error, Temperature, Security, natural log of Exchange rate, Inflation and Agricultural output respectively.

Source: Author’s computation 2025, using Eviews

In the first period, agricultural output is almost entirely driven by its own innovations, accounting for approximately 90.8% of the forecast error variance. This high initial self-dependence suggests a strong degree of short run inertia in the agricultural sector, where current outcomes are largely shaped by past performance. However, as the forecast horizon extends, the explanatory power of agricultural output’s own shocks

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume IX Issue XV September 2025 | Special Issue on Economics

diminishes considerably, falling to 56.0% by the tenth period. This declining trend indicates that over time, agricultural output becomes increasingly influenced by external shocks rather than internal dynamics.

Among the other variables, temperature emerges as the most significant contributor to the forecast variance of agricultural output, accounting for approximately 19.1% by the tenth period. The influence of temperature shocks increases remarkably after the second period and stabilises over time. This finding reaffirms the climate sensitivity of agricultural output, where fluctuations in temperature can significantly affect productivity, yield quality, and the overall viability of agricultural activities.

Inflation is the second most influential factor, contributing approximately 14.7% to the variance in agricultural output by period ten. This increasing influence over time likely reflects the cost-side pressures and price instability that inflation imposes on the agricultural sector, affecting both input costs and producer price expectations. Rising inflation can erode real returns for farmers, disrupt investment in the sector, and reduce consumer purchasing power, all of which can adversely impact output levels.

The contributions of exchange rate and security are relatively modest but non-negligible. By the tenth period, exchange rate shocks account for approximately 5.3%, while security shocks contribute around 4.9% of the forecast error variance in agricultural output. These findings suggest that while agriculture is somewhat exposed to external price fluctuations, possibly through trade exposure or the cost of imported inputs, the overall impact is less pronounced compared to temperature and inflation. Similarly, the influence of security shocks, though moderate, underscores the role of socio-political stability in enabling consistent agricultural activity, especially in regions prone to conflict or unrest.

Overall, the increasing importance of temperature and inflation shocks implies that agricultural performance is highly vulnerable to environmental and price-related risks. Therefore, proactive climate adaptation measures and sound macroeconomic management, especially inflation control, are critical to ensuring long-term agricultural sustainability and food security.

CONCLUSION

The analysis reveals that agricultural output in Nigeria is jointly and dynamically determined by both supply and demand shocks. The SVAR analysis revealed that supply shocks (particularly temperature/climate shocks) had more significant and immediate effects on agricultural output over demand shocks; though relevant, but manifested with a lag and were relatively less volatile. This is in line with the findings of Barros et al. (2009) that suggested Brazilian agricultural output growth to be highly dependent on supply shocks over demand shocks. Climate and inflation remained the most influential shocks, reflecting the dual vulnerability of Nigeria's agricultural sector to environmental and macroeconomic conditions. Hence, these results underscore the need for climate-resilient agricultural practices and macroeconomic stability to enhance productivity and food security.

However, an important limitation of this study is its focus on macro-level shocks without validating results against micro-level evidence from farmers. Structural challenges such as insecure land tenure, poor rural infrastructure, limited access to modern inputs and weak extension services also critically shape agricultural output and may interact with climatic and inflationary shocks in complex ways. Future research could therefore adopt a mixed-methods approach, complementing econometric analysis with farmer surveys, participatory studies, or case analyses to provide deeper insights. Also incorporating structural variables such as land access, irrigation use and input markets into econometric frameworks would further strengthen policy relevance and ensure that interventions address both systemic shocks and institutional bottlenecks.

Policy Recommendations

Based on the empirical findings of this study, the following policy interventions are recommended to address the dynamic interaction of demand-side and supply-side shocks on agricultural output in Nigeria.

The government should promote adaptive agricultural technologies and integrate scenario-based climate forecasting into planning. This approach, supported by stronger agro-meteorological forecasting and early warning systems, will enable farmers and policymakers to anticipate diverse climate outcomes, make informed decisions, and build resilience against climate-related risks.

Government should increase funding and targeted interventions that are needed to stabilise conflict-prone zones. Collaboration with traditional leaders, religious institutions, and civil society organisations is essential to promote dialogue, while farmer-led local security watch groups should be supported to work alongside law enforcement.

The Central Bank should adopt a stronger inflation-targeting framework supported by prudent macroeconomic policies. At the same time, price stabilisation measures such as buffer stock operations and minimum support prices for staple crops should be implemented to reduce volatility in input and output markets.

Government should adopt strategic approaches that promotes local input substitution by offering fiscal incentives such as tax holidays and reduced tariffs, hence stimulating domestic production of fertilizers, equipment, and seed technologies. Investment in agricultural research and innovation should also be expanded, while maintaining a stable and transparent exchange rate regime to provide predictability for producers.

Finally, translating these findings into effective interventions calls for active involvement of key stakeholders. Agricultural extension officers, farmer cooperatives, and local security agencies should collaborate in rolling out climate-smart farming initiatives, stabilising food prices, and promoting resilience measures that are directly responsive to farmers' practical challenges.

REFERENCES

1. Adekunle, W., & Ndukwe, C.I. (2018, July). The impact of exchange rate dynamics on agricultural output performance in Nigeria. (MPRA Paper No. 87750). https://mpra.ub.uni-muenchen.de/87750/
2. Aina, I.V., Falola, A., Amoussou, P.J., Oni, M.A., & Aribisala, T. (2019). The effect of population growth on the agricultural production in Nigeria (1961-2013). Croatian Journal of Food Science and Technology, 11(2), 230-236. https://doi.org/10.17508/CJFST.2019.11.2.12
3. Awolaja, O. G. & Okedina, I. M (2020) Investigating the asymmetric effect of exchange on agricultural output in Nigeria, 1981 - 2017. Central Bank of Nigeria, Economic and Financial Review, 58(4), 41 – 62. https://www.researchgate.net/publication/366345250
4. Aye, G.C and Odhiambo, N.M. (2021). Threshold effect of inflation on agricultural growth: Evidence from developing countries. Advances in Decision Sciences; Taichung, 25 (2), 1-22. https://iads.site/wp-content/uploads/papers/2021/Threshold-Effect-of-Inflation-on-Agricultural-Growth-Evidence-from-Developing-Countries.pdf
5. Barros, G. S., Spolador, H. F. S., & Bacchi, M. R. P. (2009). Supply and demand shocks and the growth of the Brazilian agriculture. Revista Brasileira De Economia, 63(1), 35–50. https://doi.org/10.1590/S0034-71402009000100003
6. Dimelu, M.U, Salifu, D.E., Enwelu, A.I. & Igbokwe, E.M. (2017), Challenges of herdsmen-farmers conflict in livestock production in Nigeria: experience of pastoralists in Kogi State, Nigeria. African Journal of Agricultural Research, 12(8), 642-650. https://doi.org/10.5897/AJAR2016.11740
7. Ewubare, D.E., & Iyabode, A. (2020) Determinants of Agricultural Production and Agricultural Sector Output in Nigeria. Journal of Economics & Management Research. SRC/JESMR, 1(1), 1-9. https://doi.org/10.47363/JESMR/2020(1)101
8. FAO, Food and Agriculture Organization of the United Nations. (2024). GIEWS - Global Information and Early Warning System. https://www.fao.org/giews/countrybrief/country.jsp?code=NGA
9. Gavrilova, N.G. (2021). Challenges and opportunities in Nigeria's agricultural sector. European Proceedings of Social and Behavioural Sciences, 556-562. https://doi.org/10.15405/epsbs.2021.07.67
10. Henry, C. E., Kingsley, O. O., & Nnachi, C. O. (2022). Determinants of agribusiness output in Nigeria: an empirical analysis. Amity Journal of Management Research ADMAA 1 (1), (1-19). https://www.researchgate.net/publication/361374990

11. Ketema, A.M. (2020). Determinants of agricultural output in Ethiopia: ARDL approach to co-integration. International Journal of Business and Social Research, 10(3), 1-10. http://doi.org/10.18533/ijbsr.v10i3.1293
12. McArthur, J.W. & McCord, G.C. (2017). Fertilizing Growth: Agricultural inputs and their effects in economic development. Journal of Development Economics, 127(C), 133-152. http://dx.doi.org/10.1016/j.jdeveco.2017.02.007
13. Momoh, A., Isere, V., Oshuare, M., & Al-hassan, A. (2023). Monetary policy and agricultural sector output in Nigeria. International Journal of Law, Politics & Humanities Research, 27(6), 128 -148. https://www.cambridgenigeriapub.com/wp-content/uploads/2023/04/CJLPHR_VOL27_NO6_MAR-2023-12.pdf
14. Muhammad, Q., Yanping, Z., Mansi, W., Yuyuan, Y., Shijie, L., Wasim, A., Saleh, N. M., Shaban, R.M.S., & Jiawei, G., (2023). Advancements in technology and innovation for sustainable agriculture: Understanding and mitigating greenhouse gas emissions from agricultural soils. Journal of Environmental Management, 347 (119147) https://doi.org/10.1016/j.jenvman.2023.119147
15. Ngobeni, E., & Muchopa, C.L. (2022). The impact of government expenditure in agriculture and other selected variables on the value of agricultural production in South Africa (1983-2019): Vector Autoregressive Approach. Economies, 10(9), 205- https://doi.org/10/3390/economies10090205
16. Nimo, M.K. (2012). Agricultural productivity and supply responses in Ghana. A thesis submitted to the University of Nottingham for the degree of Doctor of Philosophy. https://www.semanticscholar.org/paper/Agricultural-productivity-and-supply-responses-in-Nimo/15be06ba18a3eb9dd97bbc9dbe4bfd991558b1e5
17. Nyamida, L.O.O. (2023). Assessment study of the challenges of insecurity on economic activities of rural communities in Okehi local government area of Kogi state. African Journal of Business and Economic Development, 3(4), 38-54. https://www.ijaar.org/ajbed
18. Obi-Nwosu,V., Ananwude, A. C., & Ezeaku, C.N. (2022). The effect of commercial banks credit on agricultural sector's contribution to Real Gross Domestic Product: evidence from Nigeria 1986 to 2020. International Journal of Trend in Scientific Research and Development (IJTSRD), 6(2), 458-465. https://www.ijtsrd.com/papers/ijtsrd49229.pdf
19. Odey, F. I., Owan, J. O., & Owan, J. N. (2023). Exchange rate dynamics and agricultural sector performance nexus: The Nigerian experience. IIARD International Journal of Economics and Business Management, 9 (8), 149-164. https://doi.org/10.56201/ijebm.v9.no8.2023.pg149.167
20. OECD (2016). Agricultural Outlook 2016-2025. https://www.oecd.org/en/publications/oecd-fao-agricultural-outlook-2016_agr_outlook-2016-en.html
21. Ogunjimi, J. (2020).Exchange rate dynamics and sectoral output in Nigeria: a symmetric and asymmetric approach. American Journal of Social Sciences and Humanities, 5, (1), 178-193. https://doi.org/10.20448/801.51.178.193
22. Olalekan, A. (2019). Evolution of agriculture in Nigeria. https://www.crop2cash.com.ng/blog/evolution-of-agriculture-in-nigeria/
23. Oruonye, E.D., Altayar, Y., & Yasra, Y. (2020). Impact of farmers/herders conflict on food security in Nigeria: A case study of Taraba state Nigeria. Scholars Journal of Arts, Humanities and Social Sciences, 8(3), 154-163. https://doi.org/10.36347/sjahss.2020.v08i03.006
24. Salisu, T.Q., & Alamu, O. K. (2023). Effect of Bank Lending on Agricultural Output in Nigeria From 1981 – 2021 (Autoregressive Distribution Approach). https://doi.org/10.21203/rs.3.rs-3235799/v1
25. Steensland, A., & Zeigler, M. (2021). Productivity in Agriculture for a Sustainable Future. In Hugo, C (Eds.), the innovation revolution in agriculture: A roadmap to value creation (1st ed., 33-69). Springer Cham. https://doi.org/10.1007/978-3-030-50991-0
26. Toriola, A.K. (2022). Effects of agricultural commodity prices on agricultural output in Nigeria. Journal of Economic Impact, 4 (3), 170-176. https://doi.org/10.52223/jei4032203
27. World Bank (2024). Employment in agriculture (% of total employment) (modeled ILO estimate) – Nigeria. https://data.worldbank.org/indicator/SL.AGR.EMPL.ZS?locations=NG

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume IX Issue XV September 2025 | Special Issue on Economics

APPENDIX

Covariance Analysis: Ordinary
Date: 08/25/25 Time: 20:14
Sample: 1981 2023
Included observations: 43

Correlation Probability	AGOPT	TEMP	SECR	LNEXR	INFL
AGOPT	1.000000				

TEMP	0.231238	1.000000			
	0.1357	-----			
SECR	-0.351513	-0.064460	1.000000		
	0.0208	0.6813	-----		
LNEXR	0.527305	0.571911	-0.357570	1.000000	
	0.0003	0.0001	0.0186	-----	
INFL	0.049251	-0.523739	-0.304965	-0.194643	1.000000
	0.7538	0.0003	0.0468	0.2110	-----

Unit Root Test Result

LEVEL

Null Hypothesis: AGOPT has a unit root

Trend Specification: Trend and intercept

Break Specification: Trend and intercept

Break Type: Innovational outlier

Break Date: 2006

Break Selection: Minimize Dickey-Fuller t-statistic

Lag Length: 1 (Automatic - based on Akaike information criterion, maxlag=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.919257	< 0.01
Test critical values:	1% level	-5.719131	
	5% level	-5.175710	
	10% level	-4.893950	

*Vogelsang (1993) asymptotic one-sided p-values.

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume IX Issue XV September 2025 | Special Issue on Economics

LEVEL

Null Hypothesis: TEMP has a unit root
Trend Specification: Trend and intercept
Break Specification: Trend and intercept
Break Type: Innovational outlier

Break Date: 1997
Break Selection: Minimize Dickey-Fuller t-statistic
Lag Length: 0 (Automatic - based on Akaike information criterion, maxlag=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.990396	< 0.01
Test critical values:	1% level	-5.719131	
	5% level	-5.175710	
	10% level	-4.893950	

*Vogelsang (1993) asymptotic one-sided p-values.

LEVEL

Null Hypothesis: SECR has a unit root

Trend Specification: Trend and intercept

Break Specification: Trend and intercept

Break Type: Innovational outlier

Break Date: 1997

Break Selection: Minimize Dickey-Fuller t-statistic

Lag Length: 0 (Automatic - based on Akaike information criterion, maxlag=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.138887	< 0.01
Test critical values:	1% level	-5.719131	
	5% level	-5.175710	
	10% level	-4.893950	

*Vogelsang (1993) asymptotic one-sided p-values.

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume IX Issue XV September 2025 | Special Issue on Economics

LEVEL

Null Hypothesis: LNEXR has a unit root
Trend Specification: Trend and intercept
Break Specification: Trend and intercept
Break Type: Innovational outlier

Break Date: 1998
Break Selection: Minimize Dickey-Fuller t-statistic
Lag Length: 8 (Automatic - based on Akaike information criterion, maxlag=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-9.720634	< 0.01
Test critical values:	1% level	-5.719131	
	5% level	-5.175710	
	10% level	-4.893950	

*Vogelsang (1993) asymptotic one-sided p-values.

LEVEL

Null Hypothesis: INFL has a unit root				
Trend Specification: Trend and intercept				
Break Specification: Trend and intercept				
Break Type: Innovational outlier				
Break Date: 1997				
Break Selection: Minimize Dickey-Fuller t-statistic				
Lag Length: 8 (Automatic - based on Akaike information criterion,				
maxlag=9)				
			t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic			-5.786960	< 0.01
Test critical values:	1% level		-5.719131	
	5% level		-5.175710	
	10% level		-4.893950	

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume IX Issue XV September 2025 | Special Issue on Economics

*Vogelsang (1993) asymptotic one-sided p-values.

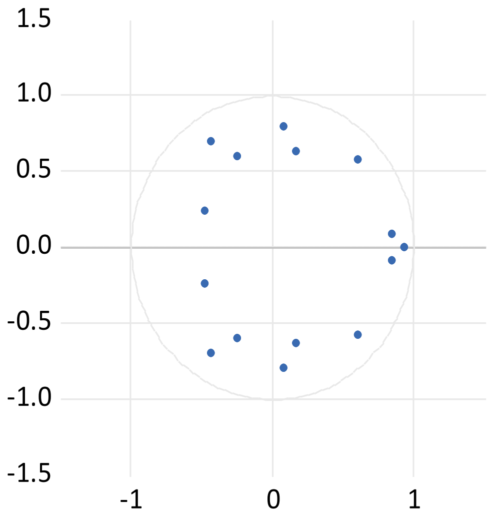
Lag Length Selection Criteria

~~VAR Lag~~ Order Selection Criteria
Endogenous variables: TEMP SECR LNEXR INFL AGOPT
Exogenous variables: C
Date: 07/28/25 Time: 12:17
Sample: 1981 2023
Included observations: 40

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-314.8295	NA	6.062609	15.99147	16.20258	16.06780
1	-202.1562	191.5446	0.076522	11.60781	12.87447*	12.06579
2	-172.3289	43.24953	0.063909	11.36644	13.68865	12.20608
3	-134.8937	44.92219*	0.040429*	10.74469*	14.12245	11.96598*

Stability Test

Inverse Roots of AR Characteristic Polynomial



Serial Correlation LM Test Result

VAR Residual Serial Correlation LM Tests
Date: 07/28/25 Time: 10:52
Sample: 1981 2023
Included observations: 40

Null hypothesis: No serial correlation at lag h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	21.99584	25	0.6360	0.863421	(25, 57.2)	0.6486
2	24.71594	25	0.4784	0.990695	(25, 57.2)	0.4932
3	19.94665	25	0.7496	0.770812	(25, 57.2)	0.7595

Null hypothesis: No serial correlation at lags 1 to h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	21.99584	25	0.6360	0.863421	(25, 57.2)	0.6486
2	61.59599	50	0.1259	1.298634	(50, 49.0)	0.1810
3	85.57809	75	0.1894	1.035030	(75, 28.2)	0.4753

*Edgeworth expansion corrected likelihood ratio statistic.

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume IX Issue XV September 2025 | Special Issue on Economics

Structural VAR Estimate Result

Structural VAR Estimates
Date: 07/28/25 Time: 12:35
Sample (adjusted): 1984 2023
Included observations: 40 after adjustments
Estimation method: Maximum likelihood via Newton-Raphson (analytic derivatives)
Convergence achieved after 21 iterations
Structural VAR is just-identified

Model: Ae = Bu where E[uu']=I

A =

1	0	0	0	0
C(1)	1	0	0	0
C(2)	C(5)	1	0	0
C(3)	C(6)	C(8)	1	0
C(4)	C(7)	C(9)	C(10)	1

B =

C(11)	0	0	0	0
0	C(12)	0	0	0
0	0	C(13)	0	0
0	0	0	C(14)	0
0	0	0	0	C(15)

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	0.066575	0.061195	1.087906	0.2766
C(2)	-0.106027	0.150009	-0.706803	0.4797
C(3)	7.659720	7.681876	0.997116	0.3187
C(4)	-1.007121	1.463052	-0.688370	0.4912
C(5)	-0.408700	0.381980	-1.069952	0.2846
C(6)	36.77198	19.71610	1.865074	0.0622
C(7)	-5.184415	3.867135	-1.340634	0.1800
C(8)	6.012986	8.046804	0.747251	0.4549
C(9)	1.957800	1.524385	1.284321	0.1990
C(10)	0.019320	0.029746	0.649493	0.5160
C(11)	0.223878	0.025030	8.944271	0.0000
C(12)	0.086648	0.009688	8.944271	0.0000
C(13)	0.209329	0.023404	8.944271	0.0000
C(14)	10.65326	1.191071	8.944271	0.0000
C(15)	2.004211	0.224078	8.944271	0.0000

Log likelihood -185.9763

Estimated A matrix:

1.000000	0.000000	0.000000	0.000000	0.000000
0.066575	1.000000	0.000000	0.000000	0.000000
-0.106027	-0.408700	1.000000	0.000000	0.000000
7.659720	36.77198	6.012986	1.000000	0.000000
-1.007121	-5.184415	1.957800	0.019320	1.000000

Estimated B matrix:

0.223878	0.000000	0.000000	0.000000	0.000000
0.000000	0.086648	0.000000	0.000000	0.000000
0.000000	0.000000	0.209329	0.000000	0.000000
0.000000	0.000000	0.000000	10.65326	0.000000
0.000000	0.000000	0.000000	0.000000	2.004211

Estimated S matrix:

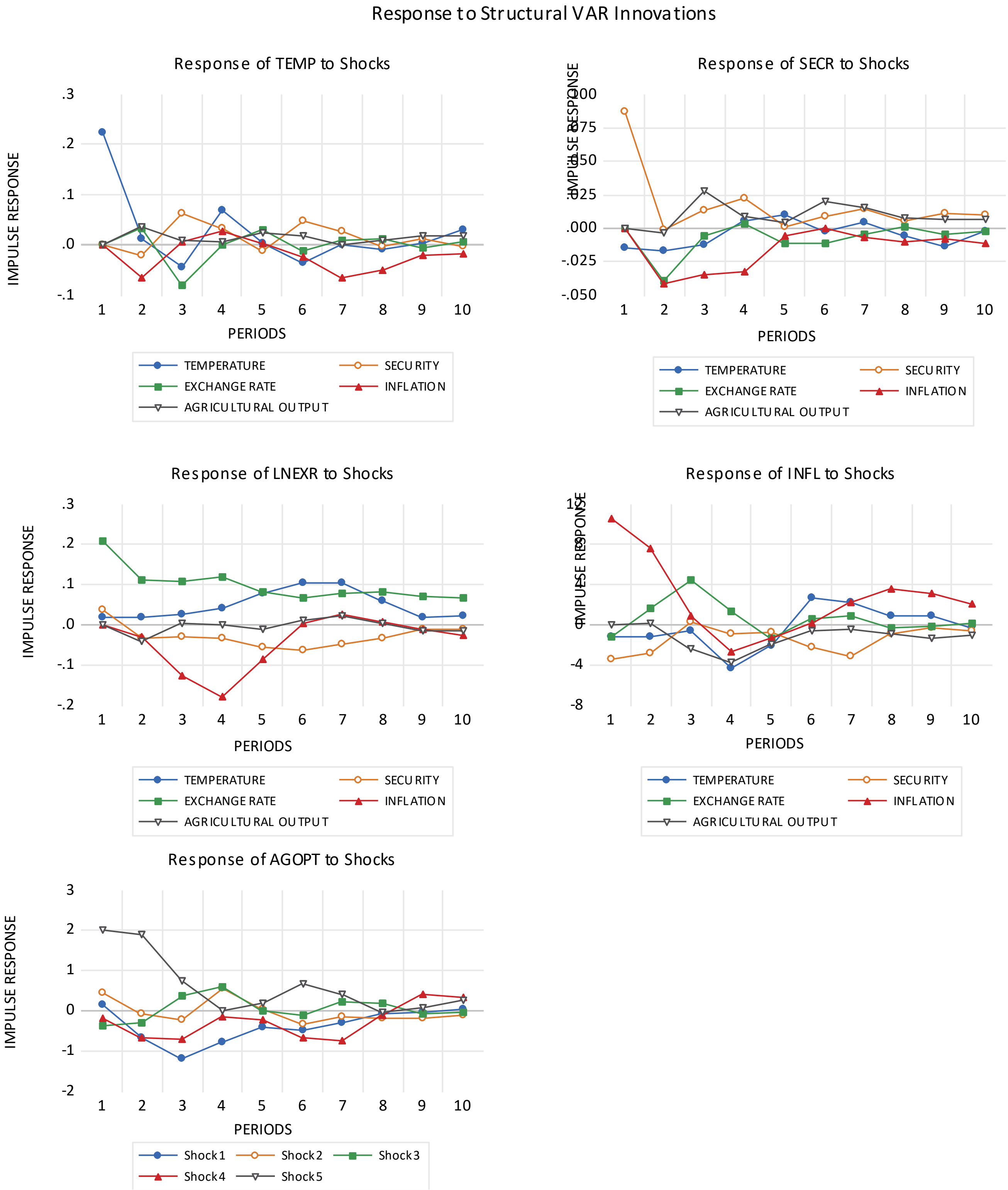
0.223878	0.000000	0.000000	0.000000	0.000000
-0.014905	0.086648	0.000000	0.000000	0.000000
0.017646	0.035413	0.209329	0.000000	0.000000
-1.272878	-3.399159	-1.258691	10.65326	0.000000
0.138246	0.445559	-0.385506	-0.205820	2.004211

Estimated F matrix:

0.319781	0.116233	0.144184	-0.334307	0.212011
-0.072081	0.183649	-0.077168	-0.202944	0.143408
1.195275	-0.740818	1.979338	-0.763021	-0.165791
-3.976706	-14.92214	2.079388	31.78986	-18.22474
-4.992861	-0.624154	-0.322442	-1.332530	5.477830

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume IX Issue XV September 2025 | Special Issue on Economics

Impulse Response Result



ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume IX Issue XV September 2025 | Special Issue on Economics

Forecast Error Variance Decomposition (FEVD) Result

Variance Decomposition of TEMP:

Period	S.E.	TEMP	SECR	LNEXR	INFL	AGOPT
1	0.223878	100.0000	0.000000	0.000000	0.000000	0.000000
2	0.239212	87.89481	0.723794	1.871894	7.286985	2.222519
3	0.264607	74.55347	6.392400	11.06487	6.025168	1.964094
4	0.276768	74.24401	7.332392	10.11469	6.463119	1.845789
5	0.279741	72.68812	7.383166	11.11799	6.333934	2.476784
6	0.287901	70.20300	9.758593	10.68568	6.682699	2.670030
7	0.296421	66.22791	9.983728	10.14816	11.12143	2.518765
8	0.301345	64.17507	9.677271	9.993809	13.60588	2.547972
9	0.303140	63.43098	9.757276	9.918370	13.97402	2.919354
10	0.305760	63.34323	9.595800	9.791633	14.05450	3.214842

Variance Decomposition of SECR:

Period	S.E.	TEMP	SECR	LNEXR	INFL	AGOPT
1	0.087921	2.873817	97.12618	0.000000	0.000000	0.000000
2	0.106246	4.515083	66.52349	13.49793	15.36999	0.093506
3	0.116839	4.783530	56.39851	11.45551	21.63217	5.730278
4	0.123954	4.449453	53.40195	10.23015	26.29411	5.624333
5	0.125153	5.047781	52.38667	10.92532	26.00160	5.638632
6	0.127600	4.902451	50.82957	11.33890	25.01449	7.914587
7	0.129606	4.858947	50.50305	11.11057	24.51415	9.013288
8	0.130395	5.000408	50.03434	10.98091	24.77604	9.208305
9	0.132135	6.007534	49.46449	10.81220	24.48896	9.226812
10	0.133241	5.944238	49.21551	10.67903	24.82464	9.336580

Variance Decomposition of LNEXR:

Period	S.E.	TEMP	SECR	LNEXR	INFL	AGOPT
1	0.213035	0.686078	2.763273	96.55065	0.000000	0.000000
2	0.249748	1.101114	3.995126	90.76635	1.450949	2.686461
3	0.302682	1.428527	3.705112	74.27501	18.75356	1.837788
4	0.375347	2.131444	3.223375	58.19582	35.25244	1.196922
5	0.405265	5.510763	4.634236	54.05027	34.67962	1.125111
6	0.428889	10.89641	6.236111	50.81560	30.96719	1.084695
7	0.452546	15.22619	6.794948	48.64894	28.11169	1.218238
8	0.464901	15.97275	6.970796	49.22949	26.66517	1.161792
9	0.471226	15.72677	6.858738	50.18064	26.00195	1.231904
10	0.477727	15.54259	6.731513	50.76437	25.63615	1.325377

Variance Decomposition of INFL:

Period	S.E.	TEMP	SECR	LNEXR	INFL	AGOPT
1	11.32478	1.263320	9.009138	1.235318	88.49222	0.000000
2	14.06849	1.619854	9.827198	2.046025	86.50154	0.005387
3	14.98905	1.583268	8.689671	10.79229	76.50579	2.428975
4	16.36219	8.382560	7.638269	9.657095	67.04029	7.281782
5	16.75051	9.662935	7.501205	9.887967	64.63192	8.315970
6	17.15084	11.75940	8.987237	9.570522	61.65230	8.030546
7	17.74354	12.65494	11.51522	9.184619	59.07757	7.567642
8	18.16974	12.30953	11.24801	8.795615	60.17578	7.471054
9	18.50786	12.11937	10.86884	8.481012	60.84112	7.689648
10	18.67263	11.93629	10.76246	8.337123	61.07655	7.887581

Variance Decomposition of AGOPT:

Period	S.E.	TEMP	SECR	LNEXR	INFL	AGOPT
1	2.103681	0.431864	4.485917	3.358170	0.957228	90.76682
2	3.011814	5.107997	2.250857	2.645286	5.401697	84.59416
3	3.427311	16.47512	2.141573	3.254393	8.322112	69.80680
4	3.608475	19.42300	4.263365	5.620616	7.719536	62.97348
5	3.644617	20.37827	4.189338	5.509720	7.980401	61.94227
6	3.811760	20.26448	4.553798	5.114962	10.28164	59.78511
7	3.926362	19.67709	4.410852	5.175154	13.28449	57.45241
8	3.938624	19.58069	4.624222	5.388370	13.30198	57.10473
9	3.967399	19.30206	4.815128	5.349552	14.21968	56.31358
10	3.990833	19.08666	4.858021	5.304737	14.73179	56.01879

Cholesky One S.D. (d.f. adjusted)
Cholesky ordering: TEMP SECR LNEXR INFL AGOPT