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Analysis of How Global Commodity Shocks Affect Nigeria's Economic Stability Based on Impulse Response Function

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Abstract: This study employs the impulse response function to investigate the impact of global commodity shocks on Nigeria's economic stability. Specifically, determine how commodity prices affect copper, maize, and oil – along with the Common Commodity Price Factor (CCPF) and global factors (GF). Monthly time series data from April 1971 to July 2024 were obtained from the Central Bank of Nigeria (www.cbn.org.ng). Analysis of impulse responses reveals that CCPF exhibits a strong reaction to its own shocks, influencing how copper and global factors impact general commodity trends. Sharp reactions in copper prices occur due to internal shocks and worldwide trends, while maize and oil prices react significantly but temporarily to both global and specific commodity shocks. Additionally, global factors are heavily shaped by industrial commodities, especially copper, which underscores their importance in reflecting global economic expectations. These results highlight the interconnectedness and persistence within commodity markets, indicating Nigeria's exposure to external disturbances. Model evaluations indicate stability, non-normal error patterns, and the effectiveness of Bayesian estimation when compared to traditional VAR models. These outcomes underscore the need for fiscal safety nets, diversification efforts, and early warning indicators—especially regarding copper and oil prices—for the effective development of macroeconomic policy in Nigeria.

Keywords: Commodity Prices; Impulse Response Function; Common Commodity Price Factor (CCPF); Global Factors; Economic Stability; Global Commodity Shocks; Commodity Trends.

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1. Introduction

Global commodity markets have a significant impact on the economic trajectories of nations that heavily rely on natural resources. Price changes in essential commodities, such as oil, copper, and agricultural goods, can create shocks that ripple through local economies, affecting inflation rates, exchange rates, government budgets, and overall economic stability. Countries that export commodities, such as Nigeria, have historically faced challenges related to these external shocks, which have hindered sustainable growth, diversification, and the effectiveness of policies [1]. Nigeria is particularly vulnerable to global price fluctuations due to its reliance on crude oil exports. A large portion of the government's revenue and foreign currency comes from oil, making the economy prone to imbalances when prices drop significantly [11]. Furthermore, commodities such as copper and maize, which are heavily dependent on global demand, also significantly impact domestic inflation and trade balances [4]. Therefore, understanding how these shocks affect Nigeria's economy is essential for crafting effective stabilisation and diversification strategies. Conventional econometric methods, mainly classical Vector

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Autoregression (VAR) models, have been commonly used to analyse the impacts of commodity price shocks [3]; [8]. However, traditional VAR methods often rely on strict assumptions regarding normality and large sample sizes, which may not apply to macro-financial data that frequently exhibit skewness, high kurtosis, and structural changes [5]. To address these issues, recent research has explored Bayesian VAR (BVAR) models that utilise prior distributions to enhance estimation accuracy and yield more dependable forecasts, even with smaller sample sizes [10]; [9].

One important product of VAR and BVAR models is the Impulse Response Function (IRF), which illustrates how a single shock to one variable influences both current and future values of other variables within the system. IRFs effectively visualise the direction, strength, and duration of shocks over time, making them particularly valuable for assessing the impact of global commodity disturbances on Nigeria's economic stability [6]. By evaluating IRFs through a Bayesian perspective, this study aims to provide deeper insights that address the challenges of classical models while capturing the dynamic risks faced by Nigeria's economy. This research confronts several important policy-related issues. It first minimises uncertainty in policy formulation by measuring the impact of global shocks on local variables. Secondly, it surpasses the statistical constraints of traditional VAR by using Bayesian methods. Thirdly, it highlights Nigeria's vulnerability to external shocks, particularly in the oil and copper markets, and suggests a framework for developing fiscal buffers. Fourthly, it identifies key leading indicators of instability, such as copper and oil prices, which policymakers should closely monitor to mitigate risks. Lastly, it confirms dynamic stability to ensure the reliability of policy actions based on the model results. Through these efforts, the study contributes to both methodological improvements and practical discussions concerning economic resilience in resource-dependent nations.

2. Methodology

In this study, we used monthly data on various factors, including the Common Commodity Price Factor, Copper, Maize, Oil Prices, and Global Factors. This information was accessed from the Central Bank of Nigeria's website (www.cbn.org.ng) and spans the timeframe from April 1971 to July 2024. All analyses were performed using EViews version 10. First, we created time plots to visualise the data, plotting years along the horizontal axis and the variable values on the vertical axis. This visualisation provided insight into the trends, movements, and variations of the data over time. Next, we calculated descriptive statistics to explore the characteristics of the data distribution. We evaluated normality using skewness, kurtosis, and the Jarque-Bera (JB) test. This JB test analyses both skewness and kurtosis to check if the data follows a normal distribution. If the JB statistic aligns with a chi-square distribution with two degrees of freedom and the p-value exceeds 0.05, we accept the null hypothesis of normality; otherwise, we reject it. Because various macroeconomic and global financial data often do not conform to normality and may be non-stationary, we performed unit root tests to determine their stationarity. The stationarity of the data was assessed through the Augmented Dickey-Fuller (ADF) test. The null hypothesis of a unit root could be rejected if the ADF statistic was significantly lower than the critical values provided by MacKinnon (1991) at the 5% significance level. Where needed, differencing was applied to ensure stationarity. After ensuring stationarity, a Bayesian Vector Autoregression (BVAR) model was specified for the six endogenous variables. The general form of the BVAR(p) model is:

$$\begin{bmatrix} \mathbf{x_{1,t}} \\ \mathbf{x_{2,t}} \\ \mathbf{x_{3,t}} \\ \mathbf{x_{4,t}} \\ \mathbf{x_{5,t}} \\ \mathbf{x_{6,t}} \end{bmatrix} = \mathbf{A_1} \begin{bmatrix} \mathbf{x_{1,t-1}} \\ \mathbf{x_{2,t-1}} \\ \mathbf{x_{3,t-1}} \\ \mathbf{x_{4,t-1}} \\ \mathbf{x_{5,t-1}} \\ \mathbf{x_{6,t-1}} \end{bmatrix} + \ldots\ldots\ldots\ldots\ldots\ldots + \mathbf{A_p} \begin{bmatrix} \mathbf{x_{1,t-p}} \\ \mathbf{x_{2,t-p}} \\ \mathbf{x_{3,t-p}} \\ \mathbf{x_{4,t-p}} \\ \mathbf{x_{5,t-p}} \\ \mathbf{x_{6,t-p}} \end{bmatrix} + \boldsymbol{\mu_p}$$

Where Xt is a 6×16 vector of endogenous variables, Ai are coefficient matrices, and $\boldsymbol{\mu_p}$is the vector of error terms with $\mathbf{A_i} \sim \mathbf{Normal}(\boldsymbol{\mu_A}, \boldsymbol{\varepsilon_A})$ and $\boldsymbol{\varepsilon_{A\sim}}\mathbf{IW}(\bar{\mathbf{S}}, \mathbf{V})$. Bayesian estimation proceeds by assigning priors to parameters. The Minnesota (Letterman) prior was adopted to shrink coefficients toward a random walk for own lags and toward zero for others, while the covariance matrix was assigned a Normal–Inverse Wishart prior: Coefficients: $\mathbf{VEC(A)} \sim \mathbf{N}(\bar{\mathbf{A}}, \boldsymbol{\Omega_A})$ and Covariance matrix: $\boldsymbol{\varepsilon_{u\sim}}\mathbf{IW}(\bar{\mathbf{S}}, \mathbf{V})$. Posterior distributions were obtained using Bayes' theorem: For the posterior distribution, using Bayes' theorem is given: $\mathbf{P}(\mathbf{A}, \boldsymbol{\varepsilon_\mu}/\mathbf{Y})\boldsymbol{\alpha}\mathbf{P}(\mathbf{Y}/\mathbf{A}, \boldsymbol{\varepsilon_\mu}) * \mathbf{P}(\mathbf{A}, \boldsymbol{\varepsilon_\mu})$ with estimation carried out using Gibbs sampling. Also, Impulse Response Functions (IRFs) were then computed to examine the dynamic interactions among the variables. An IRF traces the effect of a one-unit or one-standard-deviation shock to one endogenous variable on the current and future values of all variables in the system, holding other shocks constant. The model is given as:

$\mathbf{Y_t}$ = c + $\Phi_\mathbf{1}\mathbf{Y_{t-1}}$ + $\Phi_\mathbf{1}\mathbf{Y_{t-2}}$ + …. + $\Phi_\mathbf{p}\mathbf{Y_{t-p}}$ + $\boldsymbol{\alpha_t}$

If the system is stable:

$\mathbf{Y_t} = \mu + \psi(L)\, \boldsymbol{\alpha_1} = \mu + \boldsymbol{\alpha_{t-1}} + \psi_2\boldsymbol{\alpha_{t-2}} + \ldots.\ \psi(L) = [\Phi(L)]^{-1}$

Redating at time t + s:

$\mathbf{Y_{t+s}} = \mu + \boldsymbol{\alpha_{t+s}} + \psi_1\boldsymbol{\alpha_{t+s-1}} + \psi_2\boldsymbol{\alpha_{t+s-2}} + \ldots. + \psi_s\boldsymbol{\alpha_t} + \psi_{s+1}\boldsymbol{\alpha_{t-1}} + \ldots.$

According to Petersen and Kumar [6], the impulse response function traces the incremental effect of a 1-unit (or one standard deviation) shock in one of the variables on the future values of the other endogenous variables. Consider the VAR(p) model where; $\mathbf{Y_t = A_0 + A_1X_{t-1} + e_t}$.

Where $A_0 = \mathbf{B^{-1}\Gamma_1}$ and $\mathbf{e_t = B^{-1}\boldsymbol{\varepsilon}_t}$ A1 s

Vector error can be written as:

$$\begin{bmatrix} e_{1t} \\ e_{2t} \\ e_{3t} \\ e_{4t} \\ e_{5t} \end{bmatrix} = \frac{1}{\det(A_1)} \sum_{1=0}^{\infty} \begin{bmatrix} a_{11}a_{12}a_{13}a_{14}a_{15} \\ a_{21}a_{22}a_{23}a_{24}a_{25} \\ a_{31}a_{23}a_{33}a_{34}a_{35} \\ a_{41}a_{42}a_{43}a_{44}a_{45} \\ a_{51}a_{52}a_{53}a_{54}a_{55} \end{bmatrix}^t \text{ x adj}(A_1) \text{ x} \begin{bmatrix} e_{1t-i} \\ e_{2t-i} \\ e_{3t-i} \\ e_{4t-i} \\ e_{5t-i} \end{bmatrix}$$

Det(A_1) is a determinant value of A_1 and adj(A_1) is adjoint matrix of A_1, therefore:

$$\begin{bmatrix} x_1 \\ y_t \\ z_t \\ M_t \\ N_t \end{bmatrix} = \begin{bmatrix} \hat{x} \\ \hat{y} \\ \hat{z} \\ \widehat{M} \\ \widehat{N} \end{bmatrix} + \frac{1}{\det(A_1)} \sum_{1=0}^{\infty} \begin{bmatrix} a_{11}a_{12}a_{13}a_{14}a_{15} \\ a_{21}a_{22}a_{23}a_{24}a_{25} \\ a_{31}a_{23}a_{33}a_{34}a_{35} \\ a_{41}a_{42}a_{43}a_{44}a_{45} \\ a_{51}a_{52}a_{53}a_{54}a_{55} \end{bmatrix}^t \text{ x adj}(A_1) \text{ x} \begin{bmatrix} e_{1t-i} \\ e_{2t-i} \\ e_{3t-i} \\ e_{4t-i} \\ e_{5t-i} \end{bmatrix}$$

With element $\boldsymbol{\varphi}_{jk}(i)$:

$$\boldsymbol{\varphi}_i = \frac{1}{\det(A_1)} \sum_{1=0}^{\infty} \begin{bmatrix} a_{11}a_{12}a_{13}a_{14}a_{15} \\ a_{21}a_{22}a_{23}a_{24}a_{25} \\ a_{31}a_{23}a_{33}a_{34}a_{35} \\ a_{41}a_{42}a_{43}a_{44}a_{45} \\ a_{51}a_{52}a_{53}a_{54}a_{55} \end{bmatrix}^t \text{ x adj}(A_1)$$

That can also be written as:

$$\mathbf{Z_t} = \boldsymbol{\mu} + \sum_{1=0}^{\infty} \boldsymbol{\varphi}_i \boldsymbol{\varepsilon}_{t-1}$$

The coefficient $\varphi_{jk}(i)$ is called the Impulse Response Function (IRF). $\varphi_{jk}(i)$ plot is the best way to visualise the response to the shocks. Following Petersen and Kumar [6], the IRFs provide a visual and quantitative measure of how shocks propagate through the system, and whether effects are temporary or persistent. Plotting the IRFs, therefore, helps in identifying the magnitude, direction, and duration of responses of Nigeria's macroeconomic variables to global shocks.

3. Results

Figure 1 contains time plots of raw data. Figure 1 (CCPF) exhibits high volatility, characterised by clear upward and downward swings, indicating periods of commodity price booms and busts. Suggests non-stationary behaviour. Additionally, the Copper series exhibits sharp price spikes, which are likely due to geopolitical shocks or shifts in demand within industrial sectors. Similarly, Maize demonstrates seasonality and high variability typical of agricultural commodities. There is evidence of Strong fluctuations likely due to global economic cycles, oil supply disruptions, and OPEC decisions. The Oil Price and Global Factor series display smoother trends but still exhibit cycles of economic expansion and contraction along the timeline.

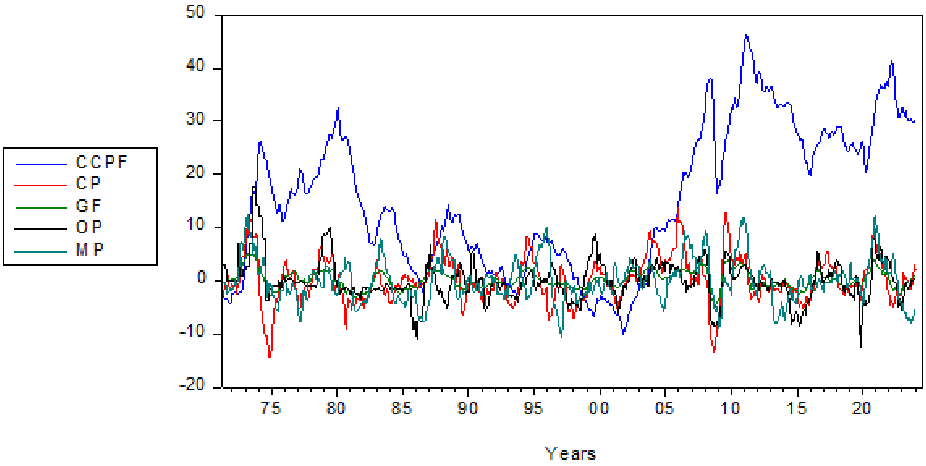

Figure 1: Time plot of Nigeria macroeconomic variables and global factors

These findings align with those of Iwayemi and Fowowe [2], who noted that oil prices are prone to frequent volatility due to geopolitical and market factors. Petersen and Kumar [6] also reported similar cyclical patterns in commodity prices, consistent with these observations.

Table 1: Descriptive statistics of Nigeria macroeconomic variables and global factors

	CCPF	CP	GF	OP	MP
Mean	15.25279	0.106893	0.165394	-0.010457	0.060331
Median	13.44000	-0.465000	-0.025000	-0.400000	-0.335000
Maximum	46.29000	13.81000	5.100000	17.70000	12.60000
Minimum	-9.990000	-14.45000	-4.900000	-12.73000	-10.73000
Std. Dev.	13.56518	4.363748	1.690954	3.839605	4.096950
Skewness	0.161535	0.157677	0.281513	0.735470	0.447017
Kurtosis	1.916816	3.841890	2.961408	5.929299	3.272180
Jarque-Bera	33.75155	21.35064	8.413355	283.8329	23.07176
Probability	0.000000	0.000023	0.014896	0.000000	0.000010
Sum	9670.270	67.77000	104.8600	-6.630000	38.25000
Sum Sq. Dev.	116481.0	12053.78	1809.952	9332.047	10624.90
Observations	634	634	634	634	634

Table 1 contains descriptive statistics. The results show that CCPF has a high standard deviation (13.56), indicating substantial volatility. Skewness values are slightly positive, suggesting right-tailed distributions. Kurtosis of Oil Price (5.93) implies leptokurtic behaviour—fatter tails than normal distribution, and Jarque-Bera test p-values (<0.05 for all) confirm that all series deviate from normality. This supports the findings of Petersen and Kumar [6], who emphasised non-normality in commodity returns. Iwayemi and Fowowe [2] further noted that skewness and kurtosis are inherent in commodity returns due to demand shocks and storage constraints.

Table 2: Unit root test of Nigeria macroeconomic variables and global factors

Variables	ADFT		RMK	PPT		RMK	KPSST		RMK
CCPF	-1.988	0.292	1(1)	-1.860	0.351	1(1)	1.088	0.014	1(1)
	-12.469	0.000		-12.485	0.000				
GF	-5.542	0.000	1(0)	-4.866	0.000	1(0)	0.073	0.0013	1(1)
OP	-5.147	0.000	1(0)	-5.866	0.000	1(0)	0.178	0.0103	
CP	-5.080	0.000	1(0)	-5.544	0.000	1(0)	0.090	0.009	1(1)
MP	-4.837	0.000	1(0)	-5.482	0.000	1(0)	0.050	0.019	1(1)

Table 2 presents the unit root tests using the Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and KPSS tests. The ADF, PP, and KPSS tests collectively confirm that the CCPF is I(1), indicating non-stationarity at levels but stationarity after first differencing. In contrast, the CP, MP, OP, and GF tests are I(0), meaning they are stationary at levels. These stationarity findings align with Sims [3], who found mixed stationarity across different commodities. Some contradict Karlsson [10], who reported that most commodity prices are I (1), which may depend on the data period and structural breaks.

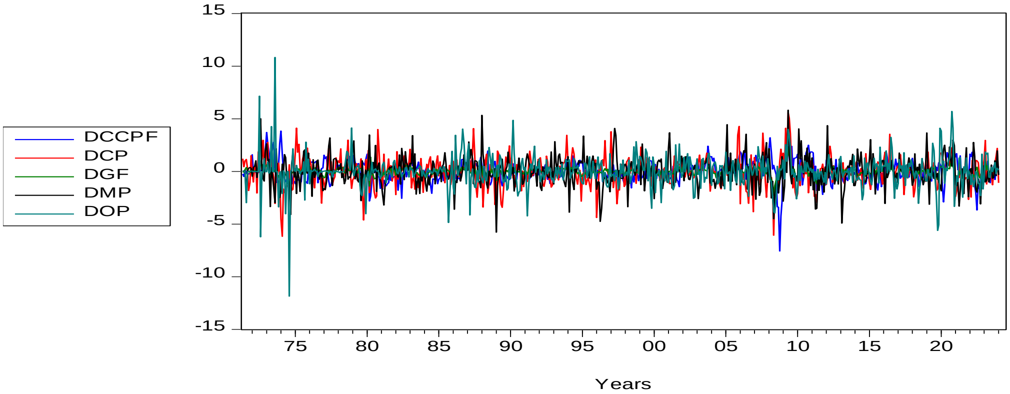

Figure 2: Time plot of Nigeria macroeconomic variables and global factors

Figure 2 contains time plots for the differenced data. All plots show series fluctuating around a mean of zero with no visible trend—confirming stationarity after differencing (particularly for CCPF). Visual confirmation aligns with the statistical evidence in Table 2. It is methodologically supported by Iwayemi and Fowowe [2], who emphasised the use of visual inspection alongside unit root testing for confirming stationarity.

Table 3: Cointegration test of Nigeria macroeconomic variables and global factors

Unrestricted Cointegration Rank Test (Trace)					**Unrestricted Cointegration Rank Test (Max. Eigenvalue)**			
Hypothesized No. of CE(s)	**Eigenvalue**	**Trace Statistic**	**0.05 Critical Value**	**Prob.****	0.234	167.8880	33.877	0.000
None *	0.234	298.544	69.819	0.000	0.081	53.093	27.584	0.000
At most 1 *	0.081	130.656	47.856	0.000	0.064	41.840	21.132	0.000
At most 2 *	0.064	77.563	29.797	0.000	0.050	32.289	14.265	0.000
At most 3 *	0.050	35.723	15.495	0.000	0.005	3.434	3.841	0.064
At most 4	0.005	3.434	3.841	0.064	0.234	167.889	33.877	0.000
Trace test indicates 4 cointegrating eqn(s) at the 0.05 level					Trace test indicates 4 cointegrating eqn(s) at the 0.05 level			
** Denotes rejection of the hypothesis at the 0.05 level*					** Denotes rejection of the hypothesis at the 0.05 level*			
***MacKinnon-Haug-Michelis (1999) p-values*					***MacKinnon-Haug-Michelis (1999) p-values*			

Table 3 contains the Cointegration Test. The results show that both the Trace and Max Eigenvalue tests indicate four cointegrating vectors at the 5% level. These suggest that, despite short-term volatility, CCPF, CP, GF, MP, and OP tend to move together in the long run. Findings confirm earlier work by Sims [3] on cointegration in financial time series and support Bańbura et al. [9], who found that commodity prices and global economic indicators are often cointegrated.

Table 4: VAR lag order selection criteria of Nigeria macroeconomic variables and global factors

VAR Lag Order Selection Criteria						
Endogenous variables: CCPF CP GF MP OP						
Exogenous variables: C						
Sample: 1971M04 2024M07						
Included observations: 626						
Lag	**LogL**	**LR**	**FPE**	**AIC**	**SC**	**HQ**
0	-8420.924	NA	337898.3	26.91989	26.95534	26.93366
1	-3978.031	8800.619	0.250531	12.80521	13.01796	12.88787
2	-3777.429	394.1538	0.142961	12.24418	12.63422	12.39573

3	-3751.133	51.24756	0.142376	12.24004	12.80737	12.46047
4	-3709.686	80.11290	0.135097	12.18750	12.93212	12.47681
5	-3677.297	62.08793	0.131960	12.16389	13.08580	12.52209
6	-3512.591	313.0997	0.084463	11.71754	12.81674	12.14462
7	-3445.852	125.8015	0.073936	11.58419	12.86068	12.08016
8	-3278.532	312.7238*	0.046937*	11.12949*	12.58328*	11.69434*

** Indicates lag order selected by the criterion*

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

FPE: Final prediction error

AIC: Akaike information criterion

SC: Schwarz information criterion

HQ: Hannan-Quinn information criterion

Table 4 contains the VAR Lag Order Selection. The results of all the criteria (AIC, SC, HQ, FPE, LR) suggest an optimal lag of 8. This high lag structure accounts for the slow dynamics and persistence in commodity markets. Similar lag selections are found in Kilian and Vigfusson, where the use of high-frequency commodity data necessitated longer lags to capture delayed responses and feedback loops [7]. The scalar equation is given as:

$$\begin{aligned}\mathbf{CCPF_t} = \mathbf{0.024} &+ \mathbf{1.045\,CCPF_{t-1}} - \mathbf{0.068CCPF_{t-2}} - \mathbf{0.066CCPF_{t-3}} - \mathbf{0.015CCPF_{t-4}} + \mathbf{0.016CCPF_{t-5}} \\ &+ \mathbf{0.033CCPF_{t-6}} + \mathbf{0.053CCPF_{t-7}} + \mathbf{0.021CP_{t-1}} - \mathbf{0.0167CP_{t-2}} - \mathbf{0.012CP_{t-3}} + \mathbf{0.013CP_{t-4}} \\ &+ \mathbf{0.020CP_{t-5}} + \mathbf{0.013CP_{t-6}} + \mathbf{0.013CP_{t-7}} + +\mathbf{0.262GF_{t-1}} + \mathbf{0.072GF_{t-2}} + \mathbf{0.105GF_{t-3}} \\ &+ \mathbf{0.116GF_{t-4}} + \mathbf{0.084GF_{t-5}} - \mathbf{0.122GF_{t-6}} - \mathbf{0.103GF_{t-7}} + \mathbf{0.0143MP_{t-1}} \\ &- \mathbf{0.007MP_{t-2}} - \mathbf{0.001MP_{t-3}} + \mathbf{0.002MP_{t-4}} + \mathbf{0.005MP_{t-5}} - \mathbf{0.007MP_{t-6}} + \mathbf{0.002MP_{t-7}} \\ &- \mathbf{0.010OP_{t-1}} - \mathbf{0.005OP_{t-2}} + \mathbf{0.009OP_{t-3}} + \mathbf{0.013OP_{t-4}} + \mathbf{0.008OP_{t-5}} - \mathbf{0.008OP_{t-6}} \\ &- \mathbf{0.008OP_{t-7}} + \mathbf{CCPF}\boldsymbol{\varepsilon}_\mathbf{t}\end{aligned}$$

$$\begin{aligned}\mathbf{CP_t} = \mathbf{0.059} &+ \mathbf{0.017\,CCPF_{t-1}} + \mathbf{0.009CCPF_{t-2}} - \mathbf{0.003CCPF_{t-3}} - \mathbf{0.006CCPF_{t-4}} - \mathbf{0.020CCPF_{t-5}} \\ &+ \mathbf{0.013CCPF_{t-6}} + \mathbf{0.010CCPF_{t-7}} + \mathbf{0.0950CP_{t-1}} - \mathbf{0.064CP_{t-2}} - \mathbf{0.019CP_{t-3}} + \mathbf{0.012CP_{t-4}} \\ &+ \mathbf{0.006CP_{t-5}} - \mathbf{0.012CP_{t-6}} - \mathbf{0.015CP_{t-7}} + \mathbf{0.621GF_{t-1}} + \mathbf{0.270GF_{t-2}} - \mathbf{0.056GF_{t-3}} \\ &- \mathbf{0.041GF_{t-4}} + \mathbf{0.041GF_{t-5}} - \mathbf{0.040GF_{t-6}} - \mathbf{0.021GF_{t-7}} - \mathbf{0.019MP_{t-1}} \\ &- \mathbf{0.005MP_{t-2}} - \mathbf{0.011MP_{t-3}} - \mathbf{0.006MP_{t-4}} + \mathbf{0.005MP_{t-5}} - \mathbf{0.003MP_{t-6}} + \mathbf{0.001MP_{t-7}} \\ &+ \mathbf{0.029OP_{t-1}} - \mathbf{0.047OP_{t-2}} + \mathbf{0.001OP_{t-3}} - \mathbf{0.007OP_{t-4}} - \mathbf{0.008OP_{t-5}} - \mathbf{0.004OP_{t-6}} \\ &- \mathbf{0.001OP_{t-7}} + \mathbf{CP}\boldsymbol{\varepsilon}_\mathbf{t}\end{aligned}$$

$$\begin{aligned}\mathbf{GF_t} = \mathbf{0.040} &+ \mathbf{0.021\,CCPF_{t-1}} - \mathbf{0.002CCPF_{t-2}} - \mathbf{0.005CCPF_{t-3}} - \mathbf{0.009CCPF_{t-4}} - \mathbf{0.008CCPF_{t-5}} \\ &- \mathbf{0.004CCPF_{t-6}} + \mathbf{0.004CCPF_{t-7}} + \mathbf{0.032CP_{t-1}} - \mathbf{0.017CP_{t-2}} - \mathbf{0.010CP_{t-3}} + \mathbf{0.001CP_{t-4}} \\ &+ \mathbf{0.001CP_{t-5}} + \mathbf{0.002CP_{t-6}} + \mathbf{0.001CP_{t-7}} + \mathbf{1.078GF_{t-1}} - \mathbf{0.056GF_{t-2}} - \mathbf{0.056GF_{t-3}} \\ &+ \mathbf{0.0022GF_{t-4}} - \mathbf{0.015GF_{t-5}} - \mathbf{0.015GF_{t-6}} - \mathbf{0.009GF_{t-7}} + \mathbf{0.011MP_{t-1}} \\ &- \mathbf{0.007MP_{t-2}} - \mathbf{0.008MP_{t-3}} + \mathbf{0.002MP_{t-4}} + \mathbf{0.002MP_{t-5}} - \mathbf{0.001MP_{t-6}} + \mathbf{0.001MP_{t-7}} \\ &- \mathbf{0.010OP_{t-1}} + \mathbf{0.010OP_{t-2}} - \mathbf{0.007OP_{t-3}} + \mathbf{0.005OP_{t-4}} - \mathbf{0.001OP_{t-5}} - \mathbf{0.003OP_{t-6}} \\ &- \mathbf{0.0004OP_{t-7}} + \mathbf{GF}\boldsymbol{\varepsilon}_\mathbf{t}\end{aligned}$$

$$\begin{aligned}\mathbf{MP_t} = \mathbf{0.009} &+ \mathbf{0.068\,CCPF_{t-1}} - \mathbf{0.050CCPF_{t-2}} + \mathbf{0.003CCPF_{t-3}} - \mathbf{0.020CCPF_{t-4}} - \mathbf{0.016CCPF_{t-5}} \\ &+ \mathbf{0.003CCPF_{t-6}} + \mathbf{0.013CCPF_{t-7}} - \mathbf{0.027CP_{t-1}} + \mathbf{0.031CP_{t-2}} - \mathbf{0.005CP_{t-3}} + \mathbf{0.005CP_{t-4}} \\ &+ \mathbf{0.004CP_{t-5}} + \mathbf{0.0138CP_{t-6}} + \mathbf{0.013CP_{t-7}} + \mathbf{0.354GF_{t-1}} - \mathbf{0.106GF_{t-2}} - \mathbf{0.151GF_{t-3}} \\ &- \mathbf{0.047GF_{t-4}} - \mathbf{0.008GF_{t-5}} + \mathbf{0.049GF_{t-6}} + \mathbf{0.040GF_{t-7}} + \mathbf{0.950MP_{t-1}} \\ &- \mathbf{0.016MP_{t-2}} - \mathbf{0.018MP_{t-3}} - \mathbf{0.014MP_{t-4}} - \mathbf{0.014MP_{t-5}} - \mathbf{0.012MP_{t-6}} - \mathbf{0.012MP_{t-7}} \\ &- \mathbf{0.038OP_{t-1}} - \mathbf{0.0260OP_{t-2}} - \mathbf{0.021OP_{t-3}} - \mathbf{0.001OP_{t-4}} - \mathbf{0.004P_{t-5}} - \mathbf{0.002OP_{t-6}} \\ &+ \mathbf{0.006OP_{t-7}} + \mathbf{MP}\boldsymbol{\varepsilon}_\mathbf{t}\end{aligned}$$

$$\begin{aligned}\mathbf{OP_t} = -\mathbf{0.011} &+ \mathbf{0.077CCPF_{t-1}} - \mathbf{0.016CCPF_{t-2}} - \mathbf{0.013CCPF_{t-3}} - \mathbf{0.023CCPF_{t-4}} - \mathbf{0.021CCPF_{t-5}} \\ &- \mathbf{0.008CCPF_{t-6}} + \mathbf{0.002CCPF_{t-7}} + \mathbf{0.025CP_{t-1}} - \mathbf{0.010CP_{t-2}} + \mathbf{0.014CP_{t-3}} - \mathbf{0.007CP_{t-4}} \\ &+ \mathbf{0.001CP_{t-5}} - \mathbf{0.004CP_{t-6}} - \mathbf{0.007CP_{t-7}} + \mathbf{0.686GF_{t-1}} - \mathbf{0.360GF_{t-2}} - \mathbf{0.178GF_{t-3}} \\ &- \mathbf{0.059GF_{t-4}} - \mathbf{0.015GF_{t-5}} + \mathbf{0.007GF_{t-6}} + \mathbf{0.027GF_{t-7}} - \mathbf{0.060MP_{t-1}} \\ &+ \mathbf{0.031MP_{t-2}} + \mathbf{0.003MP_{t-3}} + \mathbf{0.009MP_{t-4}} + \mathbf{0.019MP_{t-5}} + \mathbf{0.010MP_{t-6}} + \mathbf{0.007MP_{t-7}} \\ &+ \mathbf{0.847OP_{t-1}} + \mathbf{0.006OP_{t-2}} + \mathbf{0.010OP_{t-3}} - \mathbf{0.004OP_{t-4}} - \mathbf{0.004OP_{t-5}} - \mathbf{0.005OP_{t-6}} \\ &- \mathbf{0.006OP_{t-7}} + \mathbf{OP}\boldsymbol{\varepsilon}_\mathbf{t}\end{aligned}$$

The Bayesian VAR results indicate that each commodity price and factor relationship, with its own past values (lags), is the most important driver of current dynamics and how they influence each other, highlighting the transmission of international shocks into commodity markets. The estimates confirm both high autoregressive behaviour and meaningful interdependence among commodities through global linkages, indicating a robust and well-fitted model. The Goodness of Fit for each of the estimated Bayesian VAR equations is shown in Table 5 below.

Table 5: Goodness of fit table for the Bayesian var estimates

Parameters	CCPF	CP	GF	MP	OP
R-squared	0.997544	0.920349	0.969091	0.897427	0.873982
Adj. R-squared	0.997399	0.915632	0.967261	0.891353	0.866519
Sum sq. resids	280.0495	958.5045	55.91384	1088.015	1171.408
S.E. equation	0.688373	1.273513	0.307586	1.356825	1.407863
F-statistic	6858.331	195.1110	529.4260	147.7364	117.1086
Mean dependent	15.46069	0.118549	0.168405	0.074019	-0.029872
S.D. dependent	13.49627	4.384447	1.699938	4.116372	3.853456

The Bayesian VAR estimates in each of the equations showing – Common Commodity Price Factor (CCPF), Copper (CP), Global Factor (GF), Corn Price (MP) and Oil Price (OP) – is interpreted below according to the significance of their delayed variables (using t-statistics > |1.96| as the threshold for significance at the 5% level) and overall alignment (judged by the magnitude and persistence of own lag coefficients). The Bayesian VAR estimates for the five variables – Common Commodity Price Factor (CCPF), Copper (CP), Corn (MP), Oil Price (OP), and Global Factors (GF) – reveal distinctive patterns of interdependence and persistence. Below is the interpretation of each equation, considering the statistical significance of the parameters and the general fit, followed by a comparative discussion with previous studies.

Root	Modulus
0.989248	0.989248
0.919635 + 0.119599i	0.927380
0.919635 - 0.119599i	0.927380
0.865084	0.865084
0.832477 + 0.142380i	0.844565
0.832477 - 0.142380i	0.844565
0.578786 + 0.514721i	0.774552
0.578786 - 0.514721i	0.774552
0.607489 + 0.119856i	0.619200
0.607489 - 0.119856i	0.619200
0.164553 + 0.515508i	0.541134
0.164553 - 0.515508i	0.541134
0.540454	0.540454
0.467930 + 0.254296i	0.532564
0.467930 - 0.254296i	0.532564
0.100539 - 0.522332i	0.531920
0.100539 + 0.522332i	0.531920
0.209524 + 0.479300i	0.523096
0.209524 - 0.479300i	0.523096
0.256344 + 0.402478i	0.477180
0.256344 - 0.402478i	0.477180
0.462943	0.462943
0.016701 + 0.462124i	0.462426
0.016701 - 0.462124i	0.462426
0.137062 - 0.439428i	0.460308
0.137062 + 0.439428i	0.460308
0.283488 + 0.335738i	0.439414
0.283488 - 0.335738i	0.439414
0.389017 + 0.191077i	0.433411
0.389017 - 0.191077i	0.433411

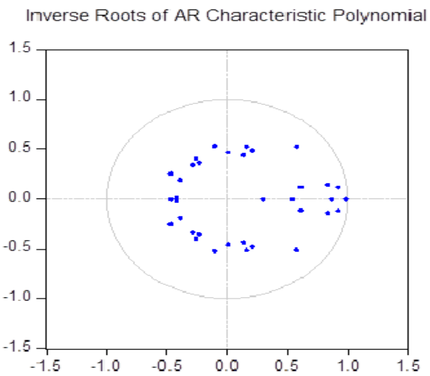

Figure 3: Dynamic stability test

Strong autoregressive dynamics characterise the equation for CCPF. The coefficient for the first layer of CCPF is highly significant and large in magnitude (1.045, t = 33.238), indicating high persistence and strong intrinsic layer effects. Delayed coefficients at positions 3 and 7 are also significant, with negative and positive effects, respectively. The global factors of delays 1, 4, and 5 have a significant impact on the CCPF, suggesting that global dynamics have a delayed yet notable effect. The R-squared value of 0.997544 and the adjusted R-squared value of 0.997399 indicate a near-perfect model fit, showing that the chosen regressors account for almost all variations in the CCPF. This strong autoregressive behaviour is consistent with the findings of Bańbura et al. [9], who observed sustained dynamics of macro-financial indicators using Bayesian VARs. The CP equation indicates moderate persistence, as evident from the very significant coefficient of CP (-1) (0.950, t = 27.479). The R-squared and adjusted R-squared values of 0.920349 and 0.915632, respectively, confirm a strong explanatory power. The global factor (GF) of delay 1 is also statistically significant (p = 0.621, t = 4.321), suggesting a notable influence of global trends on copper prices. The remaining delays of CP and other variables are mostly negligible, implying a predominant short-term feedback mechanism. This supports the findings in Bańbura et al. [9], which show that Bayesian VAR models effectively capture high-frequency market reactions, characterised by sharp initial impacts that subside rapidly. The GF equation reveals a dominant autoregressive structure in which the GF (-1) has a large and significant coefficient (1.078, t = 30.766), highlighting strong internal persistence. CCPF(-1) and CP(-1) also significantly affect GF, suggesting spillover from commodity-specific factors to global dynamics.

The R-squared value of 0.969091 and the adjusted R-squared value of 0.967261 confirm that the model effectively captures global factor dynamics. In particular, the coefficient of CP (-1) (0.032, t = 3.812) confirms the transmission of copper price shocks to the global variable. These patterns are consistent with Canova (2007), which highlighted the ability of BVAR models to capture global connections and interactions across commodity and financial markets. For the MP equation, the coefficient of MP (-1) is highly significant and almost unity (0.950, t = 29.637), signalling high inertia in corn prices. In addition, GF (-1) has a significant effect on MP (0.354, t = 2.271), suggesting that global conditions are transferred to domestic agricultural markets. The explanatory power is high with R-squared and adjusted R-squared values of 0.897427 and 0.891353, respectively. This supports the evidence presented by Koop and Korobilis [5], who observed that Bayesian VARs are particularly effective in explaining the price dynamics of agricultural commodities when global shocks are taken into account. The OP equation also exhibits high explanatory power, with an R-squared of 0.873982 and an adjusted R-squared of 0.866519. The most dominant variable is OP (-1), which is very significant and large (0.847, t = 25.047), indicating a high degree of price persistence in the oil market. GF (-1) also has a significant impact (0.686, t = 4.185), further supporting the evidence of global macroeconomic influence on oil prices.

This finding is consistent with the results of Adeniran and Sidiq [1], who employed Bayesian methods to demonstrate that sustained oil price behaviour is influenced by global economic activity. The Bayesian VAR estimates provide strong confirmation of the presence of persistence in commodity prices and interrelationships between the variables, particularly through the global factor. CCPF, GF, and MP exhibit the strongest reliance on their own layer, while copper and oil prices also react significantly to global and commodity-specific shocks. The model's excellent fit across all five equations confirms its robustness. Figure 3, the dynamic stability test, shows the Inverse Roots of the AR Characteristic Polynomial, which is a Dynamic Stability Test for a Vector Autoregression (VAR) model. Here is the interpretation of the output: the plot of the inverse roots of the AR characteristic polynomial shows the inverse roots (or eigenvalues) of the estimated VAR model in the complex plane. The unit circle (circle with radius 1) is displayed in the plot. All the blue dots (representing the inverse roots) are located strictly within the unit circle. The modulus values (which represent the magnitude of the roots) range from approximately 0.433 to 0.989, all of which are less than 1. The fact that no root has a modulus equal to or greater than 1 confirms dynamic stability. The VAR model satisfies the stability condition, as all inverse roots lie inside the unit circle. This implies that the VAR model is stationary, the estimated relationships among variables are stable over time, and the impulse response functions derived from this model are valid for interpretation.

Table 6: Impulse response function of the Bayesian var estimates

Response of CCPF					
Period	**CCPF**	**CP**	**GF**	**MP**	**OP**
1	0.673	0.000	0.000	0.000	0.000
2	0.713	0.072	0.064	0.020	-0.012
3	0.714	0.153	0.155	0.036	-0.026
4	0.678	0.248	0.282	0.049	-0.026
5	0.640	0.388	0.442	0.062	-0.013
6	0.626	0.578	0.627	0.075	0.006
7	0.640	0.734	0.771	0.078	0.004
8	0.690	0.835	0.864	0.075	-0.027
9	0.736	0.906	0.928	0.068	-0.074
10	0.767	0.955	0.972	0.059	-0.131
Response of CP					
Period	**CCPF**	**CP**	**GF**	**MP**	**OP**
1	0.087	1.241	0.000	0.000	0.000
2	0.115	1.292	0.156	-0.029	0.036
3	0.143	1.244	0.239	-0.034	0.011

4	0.169	1.166	0.295	-0.046	-0.015
5	0.186	1.094	0.322	-0.064	-0.054
6	0.180	1.026	0.328	-0.071	-0.104
7	0.153	0.936	0.317	-0.079	-0.153
8	0.123	0.822	0.293	-0.083	-0.194
9	0.093	0.705	0.258	-0.086	-0.228
10	0.065	0.590	0.216	-0.089	-0.255
Response of GF					
Period	**CCPF**	**CP**	**GF**	**MP**	**OP**
1	0.030	0.175	0.242	0.000	0.000
2	0.051	0.232	0.270	0.0123	0.012
3	0.071	0.269	0.293	0.0181	0.008
4	0.085	0.282	0.299	0.016	-0.007
5	0.091	0.286	0.295	0.011	-0.028
6	0.086	0.284	0.285	0.009	-0.050
7	0.075	0.274	0.269	0.005	-0.069
8	0.063	0.257	0.250	0.001	-0.087
9	0.051	0.235	0.228	-0.003	-0.102
10	0.040	0.209	0.202	-0.007	-0.115
Response of MP					
Period	**CCPF**	**CP**	**GF**	**MP**	**OP**
1	0.046	0.109	0.361	1.270	0.000
2	0.101	0.140	0.446	1.199	0.0489
3	0.127	0.211	0.497	1.121	0.058
4	0.150	0.251	0.498	1.023	0.036445
5	0.151	0.275	0.476	0.909	0.010448
6	0.131	0.280	0.440	0.786	-0.022929
7	0.106	0.301	0.408	0.661	-0.057249
8	0.089	0.338	0.382	0.534	-0.079572
9	0.077	0.365	0.356	0.421	-0.099939
10	0.069	0.379	0.328	0.324	-0.118973
Response of OP					
Period	**CCPF**	**CP**	**GF**	**MP**	**OP**
1	0.066	0.184305	0.448315	-0.187773	1.271959
2	0.128	0.300905	0.524299	-0.235508	1.077507
3	0.174	0.372656	0.537905	-0.224489	0.926016
4	0.208	0.428169	0.524641	-0.209963	0.800680
5	0.216	0.449149	0.503601	-0.187954	0.675911
6	0.201	0.457727	0.486164	-0.145482	0.556201
7	0.176	0.459836	0.475714	-0.094984	0.446662
8	0.151	0.449395	0.467742	-0.042885	0.345372
9	0.130	0.427649	0.450222	0.000459	0.257647
10	0.114	0.395207	0.422626	0.033543	0.180258
Cholesky Ordering: CCPF CP GF MP OP					

Table 6 contains the results of the impulse response function of the Bayesian VAR Estimates. The impulse response function (IRF) of the Bayesian VAR estimates provides insights into the dynamic interactions among the Common Commodity Price Factor (CCPF), Copper (CP), Maize Price (MP), Oil Price (OP), and Global Factors (GF). The response of CCPF to its own shock is persistently strong, beginning at 0.673 and increasing gradually to 0.767 by the tenth period. This indicates a significant internal momentum in commodity price movements. Over time, CCPF responds increasingly to shocks from CP and GF, indicating that fluctuations in these variables are transmitted into broader patterns of commodity prices. This finding supports earlier empirical work that highlights the systemic influence of key industrial commodities, such as copper, and macro-level global drivers on commodity indices. Notably, OP has a slight negative effect from periods 2 to 10, a counterintuitive pattern that may indicate hedging behaviour or structural divergences between oil prices and broader commodity movements. In the case of Copper (CP), the variable exhibits a strong and immediate reaction to its own shock, with a value of 1.241 in the first period. This self-effect gradually diminishes but remains above unity until the fifth period, underscoring the persistent inertia in the copper market. CCPF's effect on CP increases initially and peaks in the fifth period before tapering, indicating that overall commodity momentum ultimately influences copper pricing. Interestingly, global factors exert a growing influence from period 2 to 5 before stabilising, which is consistent with studies emphasising copper's sensitivity to macroeconomic cycles. The effects of MP and OP on CP are relatively minor and increasingly negative, indicating minimal spillovers or possibly substitution effects in commodity portfolios. The response of the Global Factor (GF) shows moderate sensitivity to shocks from CP and CCPF.

The initial self-shock effect of 0.242 is modest and peaks at 0.299 in period 4 before declining. CP contributes significantly to GF across all periods, suggesting that industrial commodity markets, such as copper, can serve as proxies for broader global economic expectations. The minimal and declining responses from MP and OP suggest that global macroeconomic sentiment is less affected by agricultural and energy commodities in the short to medium term, echoing previous literature that identifies base metals as more reflective of economic cycles than soft commodities or oil. Maize Price (MP) shows a sharp response to its own shock in the first period (1.270), which gradually decays to 0.324 by the tenth period. This highlights the transitory but notable influence of internal factors in the maize market. MP is highly responsive to GF and CP, especially in the early periods, with the impact of GF peaking at 0.498 by the third and fourth periods. This aligns with studies suggesting that agricultural prices are becoming increasingly linked to broader global market sentiments and industrial commodity pricing. The effect of OP is initially positive but turns increasingly negative, potentially indicating energy cost pressures or policy shifts affecting agricultural production costs over time. The dynamic influence of CP on MP is consistent with prior findings that indicate copper serving as a barometer of global demand, affecting even soft commodity markets. Oil Price (OP) reacts sharply to its own innovation, with a starting value of 1.271 and a decline to 0.180 by the tenth period.

This strong autoregressive pattern is typical of oil markets where geopolitical tensions, OPEC decisions, and supply-demand fundamentals influence pricing. GF and CP exhibit moderate and persistent positive effects, suggesting that macroeconomic expectations and industrial activity partially shape oil price dynamics. The initial negative effect of MP, especially in the early periods, is likely linked to substitution or cost-related adjustments in agricultural production. CCPF's influence on OP increases initially but gradually wanes, which may imply that while broad commodity trends affect oil prices, their impact diminishes over time. This aligns with previous studies that position oil as both a leading and lagging indicator in global commodity interactions. The results affirm much of the existing empirical literature on Bayesian VAR modelling and impulse response behaviour in commodity markets. The findings highlight the interconnectedness of industrial commodities, such as copper, global macroeconomic expectations, and broader commodity trends, as represented by the CCPF. The behaviour of maize and oil prices, although interconnected, exhibits more volatility and distinct response paths, highlighting their sensitivity to specific supply-side and geopolitical shocks.

Table 7: Granger causality test of the estimates of the Bayesian VAR model

Pairwise Granger Causality Tests			
Sample: 1971M04 2024M07			
Lags: 5			
Null Hypothesis	**Obs**	**F-Statistic**	**Prob.**
CP does not Granger-cause CCPF	629	16.5947	2.E-15
CCPF does not Granger-cause CP		1.78083	0.1147
GF does not Granger-cause CCPF	629	38.0900	4.E-34
CCPF does not Granger-cause GF		3.27354	0.0063
OP does not Granger-cause CCPF	629	6.03735	2.E-05
CCPF does not Granger-cause OP		4.75970	0.0003
MP does not Granger-cause CCPF	629	4.13104	0.0011
CCPF does not Granger-cause MP		4.28080	0.0008
GF does not Granger-cause CP	629	4.93157	0.0002
CP does not Granger-cause GF		1.30985	0.2580
OP does not Granger-cause CP	629	3.80486	0.0021
CP does not Granger-cause OP		4.80777	0.0003
MP does not Granger-cause CP	629	0.95298	0.4461
CP does not Granger-cause MP		3.55634	0.0035
OP does not Granger-cause GF	629	3.06652	0.0096
GF does not Granger-cause OP		7.75668	4.E-07

MP does not Granger-cause GF	629	0.95443	0.4452
GF does not Granger-cause MP		5.09425	0.0001
MP does not Granger-cause OP	629	1.29177	0.2657
OP does not Granger-cause MP		2.78448	0.0169

Table 7 contains the Granger Causality Test (Bayesian VAR model). To determine whether lagged values of one variable contain information that helps predict another variable. Some of the major findings are CP → CCPF exhibits strong unidirectional causality from Copper Price (CP) to Common Commodity Price Factor (CCPF), $F = 16.59$, $p < 0.00001$. Also, GF → CCPF and CCPF → GF show bidirectional causality; Global Factor (GF) and CCPF Granger-cause each other, with stronger influence from GF to CCPF. Similarly, OP ↔ CCPF and MP ↔ CCPF: Bidirectional causality exists, indicating mutual dynamic interactions. Similarly, CP ↔ OP: shows Bidirectional causality, suggesting copper and oil prices are mutually influential. Also, CP → MP: CP Granger-causes Maize Price (MP), but not vice versa, while GF → MP, but MP does not cause GF, is unidirectional, and OP → MP shows Weak unidirectional causality from oil to maize. The results imply that CCPF is significantly influenced by individual commodity prices (CP, OP, MP) and global factors (GF), affirming its integrative nature. Interdependencies between key commodities (oil, copper, and maize) suggest that shocks in one market may spill over into others. Global factors have dominant predictive power, especially for CCPF and oil prices.

Table 8: VAR residual normality tests

VAR Residual Normality Tests				
Orthogonalisation: Cholesky (Lutkepohl)				
Null Hypothesis: Residuals are multivariate normal				
Sample: 1971M04 2024M07				
Included observations: 627				
Component	**Skewness**	**Chi-sq**	**Df**	**Prob.***
1	-0.336343	11.82175	1	0.0006
2	0.024636	0.063426	1	0.8012
3	0.225036	5.292008	1	0.0214
4	0.177628	3.297151	1	0.0694
5	0.140301	2.057007	1	0.1515
Joint		22.53134	5	0.0004
Component	**Kurtosis**	**Chi-sq**	**Df**	**Prob.**
1	6.985097	414.8910	1	0.0000
2	4.542991	62.19892	1	0.0000
3	6.854975	388.2393	1	0.0000
4	4.085889	30.80540	1	0.0000
5	11.23135	1770.102	1	0.0000
Joint		2666.237	5	0.0000
Component	**Jarque-Bera**	**Df**	**Prob.**	
1	426.7128	2	0.0000	
2	62.26235	2	0.0000	
3	393.5313	2	0.0000	
4	34.10255	2	0.0000	
5	1772.159	2	0.0000	
Joint	2688.768	10	0.0000	
**Approximate p-values do not account for the coefficient*				
Estimation				

Table 8 contains the VAR Residual Normality Test. To test whether the residuals of the VAR model are normally distributed, a key assumption in classical VAR analysis, is crucial. The summary of the results shows that the skewness for component 1 is significantly skewed ($p = 0.0006$), while the others are near symmetrical. All components exhibit excess kurtosis (i.e., heavy tails), with Component 5 having the highest value (11.23). For the Jarque-Bera (JB) Tests, all components significantly deviate from normality ($p < 0.0001$), and the Joint JB Statistic: 2688.768 ($p = 0.0000$) provides strong evidence of multivariate non-normality. The residuals are not multivariate normal, violating classical VAR assumptions. This supports the Bayesian VAR approach used in your analysis, as it is more robust to non-normality and fat-tailed distributions than classical frequentist VAR.

Table 9: VAR residual heteroskedasticity tests (levels and squares)

Sample: 1971M04 2024M07					
Included observations: 627					
Joint test:					
Chi-sq	**df**	**Prob.**			
1726.058	1050	0.0000			
Individual components					
Dependent	**R-squared**	**F(70,556)**	**Prob.**	**Chi-sq(70)**	**Prob.**
res1*res1	0.357430	4.418216	0.0000	224.1085	0.0000
res2*res2	0.173438	1.666655	0.0010	108.7457	0.0021
res3*res3	0.244099	2.564950	0.0000	153.0504	0.0000
res4*res4	0.125687	1.141826	0.2125	78.80571	0.2204
res5*res5	0.172842	1.659726	0.0011	108.3717	0.0022
res2*res1	0.245443	2.583655	0.0000	153.8925	0.0000
res3*res1	0.210825	2.121908	0.0000	132.1875	0.0000
res3*res2	0.208400	2.091071	0.0000	130.6668	0.0000
res4*res1	0.248528	2.626877	0.0000	155.8272	0.0000
res4*res2	0.217155	2.203291	0.0000	136.1564	0.0000
res4*res3	0.230254	2.375947	0.0000	144.3693	0.0000
res5*res1	0.186422	1.820013	0.0001	116.8865	0.0004
res5*res2	0.196232	1.939173	0.0000	123.0376	0.0001
res5*res3	0.170823	1.636350	0.0015	107.1061	0.0029
res5*res4	0.180283	1.746894	0.0004	113.0372	0.0009

Table 9 contains the results of the VAR Residual Heteroskedasticity Test (Levels and Squares). To test for heteroskedasticity (non-constant variance) and potential cross-equation residual correlation. Joint Chi-Square with 1726.06, df = 1050, p = 0.0000 — significant evidence of heteroskedasticity in the residuals. Individual components show that significant heteroskedasticity exists in most individual residuals and their squares (especially res1, res2, res3, res5). Only res4 (res4*res4) shows weak evidence of heteroskedasticity (p = 0.2204). The presence of heteroskedasticity suggests time-varying volatility in commodity price relationships. Indicates the potential need for GARCH-type modelling or Bayesian frameworks that effectively handle variance instability. Also justifies the use of BVAR and possibly Multivariate GARCH extensions (like Diagonal BEKK or VECH), which accommodate volatility clustering.

4. Conclusion

The analysis of impulse responses from the Bayesian Vector Autoregression (BVAR) reveals a strong connection between Nigeria's macroeconomic variables and global commodity prices. This relationship varies in terms of how long shocks last and how they spread. The Common Commodity Price Factor (CCPF) responded significantly to shocks from global factors and copper, underscoring the substantial impact of industrial commodities on the economy. Notably, both copper and oil prices exhibited abrupt self-responses, showing a degree of inertia, and affected global and agricultural markets. In contrast, maize prices reacted quickly but only for a short time, demonstrating their sensitivity to conditions in copper markets and global trends, which indicates a growing integration of agricultural markets with global cycles. Although oil prices exhibited high autoregressive behaviour, they were also influenced by trends in copper and global factors, underscoring their dual role as both influencers and reactants in the global commodity landscape. These findings indicate that Nigeria's macroeconomic stability is particularly vulnerable to external shocks, especially those related to the copper and oil markets. Furthermore, global factors play a crucial role in predicting domestic and commodity-specific movements. By monitoring these relationships, impulse response functions provide policymakers with valuable insights into the timing, direction, and duration of shocks. This knowledge supports the development of strategies for maintaining stability, such as creating fiscal buffers, diversifying the economy, and incorporating BVAR forecasts into macroeconomic strategies.

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