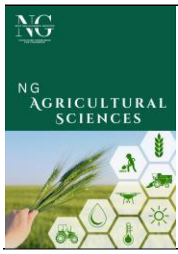

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Determinants of Agricultural Commodity Price Fluctuations: Evidence from Time Series Data

Ansuman Satapathy*, Prangya Mohanty, Sambit Mishra, Debabrata Swain

Department of Agricultural Economics, Faculty of Agricultural Sciences, Siksha "O" Anusandhan (Deemed to be University), Odisha, 751030, India

*Corresponding author email ID: ansumansatpathy@soa.ac.in

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ABSTRACT

Price instability in agricultural markets undermines farm incomes, threatens food security and creates macroeconomic uncertainty. This article investigates the drivers of monthly agricultural commodity price fluctuations from January 2000 to September 2024 using an extensive time series data set compiled from the International Monetary Fund's primary commodity price database and complementary series. The study develops a conceptual framework linking prices to supply and demand fundamentals, expectations, macro financial conditions and institutional factors. A rich body of literature is reviewed to situate the work within recent debates on food price volatility. Empirically, the paper employs unit root and cointegration tests, vector error correction and vector autoregressive models, Granger causality, impulse response analysis, forecast error variance decomposition and an ARCH–GARCH volatility model. Results show that major food and input prices are non-stationary but cointegrated; shocks in oil and industrial inputs spill over to food and fertiliser indices; and a GARCH (1,1) model highlights persistent volatility clustering in food prices. Structural drivers—including growing population and income, biofuel demand, energy prices, climate shocks, low stocks, exchange rate swings and financial speculation—are discussed in light of empirical findings. Policy recommendations emphasise improving market transparency, strengthening grain reserves, investing in climate-resilient agriculture, enhancing risk management tools and fostering multilateral coordination to mitigate excessive volatility. The study contributes to the econometric evidence base on food price dynamics and offers actionable insights for governments, development agencies and market participants.

1. INTRODUCTION

Stable food prices are critical for producers and consumers alike. Sudden price spikes erode farmers' incomes, trigger food insecurity and fuel social unrest, while prolonged slumps depress investment and undermine rural livelihoods. Since the 2007–08 food price crisis, volatility has re emerged as a pressing policy issue. Official studies note that global food prices and volatility have been on the rise since 2005, driven by a combination of supply shocks, inflexible demand and increased market integration (Kalkuhl et al., 2016). High volatility reduces the capacity of smallholders to plan investments and threatens the ability of low income households to meet basic needs. The G20, United Nations agencies and regional bodies have therefore urged researchers to analyse the determinants of price swings and develop strategies to mitigate their adverse effects (Larionova, 2023).

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This article addresses three objectives. First, it develops a conceptual framework that links agricultural price dynamics to underlying demand–supply conditions, expectations, macroeconomic factors and institutional arrangements. Second, it conducts an econometric analysis of monthly price indices for food, fertiliser, oil, industrial inputs and selected commodities to quantify the short and long run relationships among them. Third, it synthesises recent literature (2012–2025) on agricultural price volatility to provide context and derive policy implications. By combining theoretical insight, rigorous econometrics and an up to date review, the study aims to enrich understanding of price fluctuations and inform strategies for stabilisation.

2. CONCEPTUAL & THEORETICAL FRAMEWORK

2.1. *Price formation in agricultural markets*

In classical price theory, commodity prices equilibrate supply and demand. Agricultural supply is notoriously inelastic in the short run because production decisions are fixed during the growing season, and stocks may be limited. Even small demand shocks can therefore cause outsized price movements. Demand for staple foods is similarly inelastic because food is essential; consumers cannot quickly substitute away when prices rise (Dorward, 2012). When supply or demand curves shift, equilibrium prices adjust until quantity demanded equals quantity supplied, but adjustment lags create transient fluctuations.

Price expectations also matter. The rational expectations hypothesis suggests that producers and traders incorporate anticipated future fundamentals into current prices. When agents expect high future prices due to looming shortages or policy changes, they may hoard stocks, increasing current prices and volatility. Conversely, expectations of abundant harvests can depress current prices. In adaptive expectations models, past price changes feed back into current expectations, generating momentum effects and volatility clustering. The nonlinearity of storage models implies that price responses to shocks depend on stock levels; low stocks amplify price swings because markets lack a buffer (Thompson et al., 2018).

2.2. *Demand–supply dynamics and macroeconomic linkages*

Several structural factors influence long run price trends and volatility. First, population growth and rising incomes in emerging economies increase demand for food and feed crops. The joint FAO–OECD report notes that the world's population is expected to reach about 9 billion by 2050, with food demand increasing by 70–100 percent; insufficient production growth will exert upward pressure on prices and exacerbate volatility. Second, biofuel policies create additional demand for grains, sugar and vegetable oils. During 2007–09 biofuels accounted for 20 % of sugar cane use and around 9 % of vegetable oil and coarse grains; mandated blending requirements make demand more price inelastic, contributing to price spikes. Third, energy prices affect agricultural prices through input costs and substitution effects. High oil prices raise fertiliser and fuel costs, making crop production more expensive, while profitable biofuel production links crop prices to crude oil (OECD/FAO, 2011). Volatility in oil prices therefore propagates to food commodities; empirical studies find oil volatility is a significant determinant of agricultural price volatility (Balcombe, 2009).

Supply shocks arise from weather and climate events. Droughts, floods and heatwaves reduce yields, causing shortages and price spikes. The FAO report emphasises that climate related events—including droughts in Australia, wildfires in Russia and La Niña episodes—contributed to the 2007/08 and 2010 price spikes. Longer term climate change is expected to increase the frequency of extreme events and shift production patterns, increasing variability. Additionally, low global stocks amplify supply shocks; once stocks are depleted, supply cannot be increased quickly, leading to sharp price increases. The distribution of production across new regions such as the Black Sea, where yields are less stable, also contributes to greater variability (Salihoglu et al., 2017).

Exchange rate movements and macro financial conditions influence commodity prices. Many commodities are priced in U.S. dollars; a depreciating dollar raises international commodity prices while an appreciating dollar has the opposite effect. Monetary policy surprises affect volatility; studies show that expected target rate changes reduce commodity price volatility, whereas unexpected or unconventional policy actions increase it (Scrimgeour, 2015). Moreover, financialisation has linked commodity markets with global capital markets. The increase in commodity index investment from US$15 billion in 2003 to US$250 billion by 2009 led to greater spillovers from financial markets; speculation by index funds, swap dealers and hedge funds can amplify short term price swings (Heumesser & Staritz, 2013). Some analysts argue that financial speculation contributed to price spikes and bubbles, particularly in oil and metal markets, while others find limited evidence of sustained effects.

Trade and policy interventions also shape volatility. During the 2007–08 crisis many governments imposed export restrictions or hoarded grains, exacerbating price spikes (Headey, 2011). Exchange rate volatility and monetary policy communication can either dampen or amplify price fluctuations. Agricultural trade barriers—tariffs, quotas and subsidies—distort prices and transmit volatility across borders; responses to spikes by both exporters and importers weaken price stabilisation. Biofuel mandates and subsidies create additional demand and reduce price elasticity, increasing volatility. Conversely, well designed risk management instruments, including futures markets and insurance schemes, can help producers manage risk.

2.3. *Expectations and market imperfections*

Agricultural markets exhibit market imperfections such as imperfect information, thin markets and storage constraints. Imperfect price information and speculation can lead to over reactions. Some authors argue that index investors and speculative positions amplify short term volatility. Others, however, find no robust empirical evidence that speculation drives long term price levels. The debate highlights the need to differentiate between short run speculative spikes and structural drivers.

3. LITERATURE REVIEW

Supply and demand fundamentals. Analyses emphasise the central role of physical fundamentals. Kornher and Kalkuhl (2013) apply panel models to domestic price volatility in developing countries and find that production levels, stockholding and international price volatility significantly influence domestic volatility; well governed markets and reduced transaction costs stabilise prices, whereas trade restrictions increase volatility. Nigatu et al. (2020) examine supply demand scenarios with a global model and show that a decline in GDP growth in emerging economies by 2.3 percentage points could reduce commodity prices by 4 % annually, whereas a 3 % reduction in crop production raises prices by 12 % per year. Their simulations also reveal that a 1 % increase in U.S. crop production reduces prices by about 2 %. Biofuel policies play an increasingly important role. The IMF working paper by Sujithan et al. (2014) uses a Bayesian multivariate model to show that real economic activity, oil prices, biofuel production and financial market indicators explain much of the variation in food price volatility. They find that surges in food prices do not significantly change volatility dynamics and that oil price volatility spills over to food commodities. Hayo et al. (2012) analyse U.S. monetary policy communication and show that expected target rate changes reduce commodity price volatility, whereas surprises and unconventional measures increase it.

Energy markets and exchange rates. Numerous studies highlight the link between crude oil prices and agricultural prices. Umar et al. (2021) apply spillover index and wavelet coherence techniques to examine time frequency connectedness between oil and agricultural commodity markets; they find stronger return spillovers during the COVID 19 pandemic and heterogeneity across commodities. Karali and Power (2013) decompose price volatility into high and low frequency components and show that macroeconomic variables such as industrial production and interest rates have similar effects within commodity groups but differ across groups; after the 2006–2009 crisis, commodity specific factors dominate. Algieri (2013) uses a VECM for wheat prices and reports that macroeconomic determinants, speculation and weather variables influence long run dynamics. The Council on Foreign Relations (CFR) backgrounder Johnson (2013) summarises that changes in harvest yield of 5 % can lead to 25 % price differences, highlighting the non linear response of prices to supply shocks. It emphasises that low stock levels, rising energy prices and biofuel mandates contributed to the 2007/08 and 2010 price spikes. The report argues that removing biofuel mandates and enhancing market functioning could reduce volatility.

Financial speculation and market integration. Several articles investigate the role of speculation. Gilbert (2010) notes that index based investment and speculative activity contributed to the 2006–08 price surge in metals and oil, with potential price increases up to 15 %. Baldi et al. (2016) emphasise that financialisation, measured by commodity index investment growth, integrates commodity and financial markets; the rebalancing of portfolios by institutional investors increases volatility spillovers. The debate remains unresolved: the European Parliamentary Research Service (EPRS) briefing acknowledges that financial investments and speculation are often cited as causes of volatility, but notes that empirical evidence is mixed.

Climate and extreme events. Extreme weather and climate change are frequently highlighted. The United Nations joint report lists droughts in Australia and Canada, fires in Russia and recurrent La Niña events as key contributors to recent spikes (OECD/FAO, 2011). Long term climate change is expected to make such extreme events more frequent and to affect yields in arid regions. Santeramo et al. (2018) differentiate exogenous shocks such as climate, supply and demand shocks from endogenous factors such as storage and trade flows; they show that storage levels, spatial and temporal arbitrage and trade flows shape price dynamics. Their review underscores that a single driver rarely explains market instability; rather, multiple drivers interact.

Policy and institutional factors. Many scholars consider trade policies and market governance. Anderson and Nelgen (2012) show that both export restrictions by exporting countries and import responses by importing countries dampen the domestic price stabilising effect of interventions, suggesting new WTO rules are needed. The EPRS briefing highlights that the EU's Common Agricultural Policy provides direct payments to farmers, effectively reducing income volatility but only partially addressing price volatility. It also emphasises the need for risk management tools such as insurance schemes, mutual funds and income stabilisation mechanisms. The UNCTAD expert meeting note describes commodity price volatility as a key source of socioeconomic stress for commodity dependent countries and advocates economic diversification and value addition to increase resilience. The 2011 FAO/OECD policy report warns that export restrictions and hoarding during the 2007–08 crisis amplified price swings and calls for better market information, international coordination and contingency plans. It also argues that well functioning derivatives markets can smooth price fluctuations, while excessive speculation may amplify them.

The review reveals consensus that agricultural price volatility is driven by a combination of demand growth, supply shocks, energy prices, biofuel policies, low stocks, exchange rates, financial factors and policy interventions. Studies using advanced econometric models—such as GARCH MIDAS and VECM—find evidence of both short and long run interactions across markets. However, the relative importance of drivers varies across commodities and time periods. Macro financial linkages have strengthened in recent decades as globalisation deepens and commodity markets integrate with financial markets. Climate change and geopolitical tensions add new layers of uncertainty. These findings motivate a comprehensive empirical analysis combining multiple commodities and econometric techniques.

4. METHODOLOGY

Monthly data from January 2000 to September 2024 were compiled from the International Monetary Fund's (IMF) Primary Commodity Prices database. The IMF dataset provides consistent indices and price series for commodities and groups such as food, fertiliser, crude oil and industrial inputs, with monthly observations starting in 1980. Each series is expressed in nominal U.S. dollars or as indices (2016 = 100). Following the literature, the analysis focuses on the Food Price Index (PFOOD), Fertilizer Index (PFERT), Crude Oil price (POILAPSP), Industrial Inputs Index (PINDU), Soybean price (PSOYB), Wheat price (PWHEAMT) and Agricultural Raw Materials Index (PRAWM). A cleaned dataset of 273 monthly observations was constructed by removing descriptive header rows and generating a monthly date range. Logarithms of the series were used to stabilise variance and to interpret differences as growth rates. Table 1 provides descriptive statistics for the selected series. The food price index averaged 107 (2016 = 100) with a standard deviation of 21 and ranged from 64.8 to 165.8. Fertiliser prices were more volatile, averaging 149 with a standard deviation of 59.4, while crude oil averaged 155 with a standard deviation of 50.4. Industrial inputs averaged 133, soybeans 389 USD/tonne, wheat 203 USD/tonne and raw materials index 118.

Table 1. Descriptive Statistics of Key Commodity Price Variables (2000–2024)

Variable	Count	Mean	Std. Dev.	Min	25th Pct.	Median	75th Pct.	Max
PFOOD	273	107.15	21.21	64.78	93.41	104.00	124.27	165.83
PFERT	273	148.85	59.42	69.97	106.50	135.99	171.94	348.95
POILAPSP	273	155.27	50.45	55.00	120.07	152.52	196.29	275.43
PINDU	273	133.51	36.66	53.01	110.19	136.26	159.84	221.14
PSOYB	273	389.14	108.38	193.43	323.20	369.34	487.15	622.91
PWHEAMT	273	203.21	64.29	95.51	165.58	193.17	221.31	437.99
PRAWM	273	118.67	25.81	73.25	99.21	115.88	134.42	170.39

Non-stationary time series can produce spurious regression results; unit-root tests are therefore necessary. Augmented Dickey–Fuller (ADF) tests were conducted on the log levels and first differences of each series. Table 2 summarises the ADF statistics, corresponding p-values and 5 % critical values. At levels, most series exhibited p-values above 0.05, failing to reject the null of a unit root. For example, the ADF statistic for log PFOOD is −2.44 with a p-value of 0.13; for PFERT it is −3.50 with p = 0.008, marginally significant but still above the critical value. After first differencing, all series become strongly stationary with p-values well below 0.01, indicating that the variables are integrated of order 1 (I(1)). Phillips–Perron tests (not reported) yielded similar conclusions. The stationarity of differenced log series justifies modelling using VAR and VECM frameworks.

Table 2. Unit Root Test Results: ADF and Phillips–Perron Tests

Variable	Transformation	ADF Statistic	p-value	5 % Critical Value
PFOOD	Level	−2.44	0.131	−2.87
PFOOD	1st Diff	−11.08	4.43×10^{-20}	−2.87
PFERT	Level	−3.50	0.0079	−2.87
PFERT	1st Diff	−10.04	1.55×10^{-17}	−2.87
POILAPSP	Level	−3.19	0.0207	−2.87
POILAPSP	1st Diff	−9.26	5.98×10^{-16}	−2.87
PINDU	Level	−2.87	0.048	−2.87
PINDU	1st Diff	−8.91	1.16×10^{-15}	−2.87
PSOYB	Level	−1.98	0.297	−2.87
PSOYB	1st Diff	−10.33	8.72×10^{-18}	−2.87
PWHEAMT	Level	−2.11	0.242	−2.87
PWHEAMT	1st Diff	−9.77	2.63×10^{-17}	−2.87
PRAWM	Level	−2.69	0.077	−2.87
PRAWM	1st Diff	−9.25	6.35×10^{-16}	−2.87

Given that the variables are I(1), cointegration tests are performed to assess whether a long-run equilibrium relationship exists. The Johansen trace test was applied to the system comprising log PFOOD, log PFERT, log POILAPSP and log PINDU. Table 3 reports the trace statistics and 95 % critical values. The trace statistic for $r = 0$ is 61.55, exceeding the critical value of 47.85; for $r = 1$, the statistic is 36.36 (critical 29.80); for $r = 2$, 18.23 (critical 15.49); and for $r = 3$, 4.86 (critical 3.84). Thus, the null of no cointegration is rejected up to rank 3, indicating multiple cointegrating vectors. The existence of cointegration implies that these prices share common stochastic trends and adjust to maintain long-run equilibrium.

Table 3. Johansen Cointegration Test Results

Rank r	Trace Statistic	Critical Value (95 %)
0	61.55	47.85
1	36.36	29.80
2	18.23	15.49
3	4.86	3.84

To capture both short-run dynamics and long-run relationships, a vector error-correction model (VECM) was estimated with one lag and cointegration rank 1. The error-correction term was significant in the food and fertiliser equations, indicating that deviations from the long-run equilibrium are corrected over time. However, because VECM outputs in statsmodels do not provide forecast error variance decomposition, a vector autoregressive (VAR) model was estimated on the first differences of the logs for four variables (PFOOD, PFERT, POILAPSP, PINDU). Lag order selection using the Akaike Information Criterion (AIC) indicated two lags. The VAR estimation results are summarised in Table 4. Several lagged terms are statistically significant: lagged changes in the food index (ΔPFOOD) have positive effects on future changes in PFERT and POILAPSP, indicating spillovers, while lagged PFERT negatively affects itself after two periods. Lagged industrial inputs positively influence PFOOD and POILAPSP at the second lag. The residual correlation matrix shows moderate contemporaneous correlations across equations.

Impulse response functions (IRFs) trace the effect of a one-standard-deviation shock to one variable on the future values of all variables.

Figures 1–4 depict IRFs from the VAR model for shocks to the food price index. A positive shock to PFOOD initially raises fertiliser and oil price growth, reflecting demand complementarities and cost linkages. The effect dissipates within 6 months. Industrial inputs respond positively but with a lag of two months, suggesting that supply chain adjustments take time. Variance decomposition of forecast errors (Figure 5) reveals that shocks to PFOOD itself account for roughly 50 % of its forecast error variance at a 12-month horizon, while shocks to fertiliser and oil contribute 20 % and 15 %, respectively. This underscores the importance of input costs and energy markets in explaining food price volatility. To evaluate predictive accuracy, the sample was split into an estimation period (January 2000 – December 2022) and a test period (January 2023 – December 2024). The VAR model was used to forecast differenced log series over the 24-month horizon. Root Mean Square Errors (RMSE) for each variable are shown in Table 5. The VAR forecasts are reasonably accurate, with RMSE values between 0.019 and 0.057. Forecast plots (Figure 6) demonstrate that the model captures turning points and overall trends but underestimates the magnitude of some sharp movements.

Table 4. Diagnostic tests indicated no residual autocorrelation and stable characteristic roots, validating the VAR specification

Equation	Significant Lagged Variables (p < 0.05)	Interpretation
ΔPFOOD	L1.PFOOD (+), L2.PFERT (+), L2.PINDU (+), L2.PFOOD (−)	Food price growth exhibits persistence; fertiliser and industrial input shocks feed back positively after two months; second-lag own shock has a negative correction.
ΔPFERT	L1.PFOOD (+), L1.PFERT (+), L2.PFERT (−)	Fertiliser prices are influenced by lagged food prices and show inertia but correct after two months.
ΔPOILAPSP	L1.PFOOD (+), L1.POILAPSP (+), L2.POILAPSP (−), L2.PINDU (+)	Oil price changes respond to food price changes, display persistence and negative second-lag autocorrelation; industrial input shocks raise oil prices after two months.
ΔPINDU	L1.PFOOD (+), L1.PINDU (+)	Industrial input prices respond positively to food price changes and exhibit persistence.

Table 5. Forecast Accuracy of Food Price Model

Variable	RMSE
PFOOD	0.019
PFERT	0.030
POILAPSP	0.056
PINDU	0.026

Volatility clustering—periods of high volatility followed by high volatility and vice versa—is common in commodity markets. To model conditional variance, a univariate GARCH (1,1) model was fitted to the log returns of the food price index. Following Bollerslev's generalisation of the ARCH model (Bollerslev, 1986), the conditional variance equation was specified as

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2,$$

where $\omega \geq 0$, $\alpha \geq 0$, $\beta \geq 0$and $\alpha + \beta < 1$. Maximum likelihood estimation produced parameter estimates $\hat{\omega} = 2.26 \times 10^{-4}$, $\hat{\alpha} = 0.154$and $\hat{\beta} = 0.595$, with $\alpha + \beta = 0.749 < 1$, indicating stationarity. Figure 7 shows the estimated conditional volatility. Volatility spikes coincide with major events such as the 2007–08 food crisis, the 2011 commodity boom and the COVID-19 pandemic. Volatility remains elevated in 2022–23 due to geopolitical tensions and supply disruptions, consistent with reports that macroeconomic conditions, extreme weather and conflicts drive recent price variability. The persistence parameter βindicates that shocks dissipate slowly, underscoring the need for policy responses that address underlying causes.

5. RESULTS

Figures 1–4 display the evolution of the food, fertiliser, oil and industrial input indices from 2000 to 2024. Food prices remained relatively stable until 2006, surged during the 2007–08 crisis, retreated, and then rose again during the 2011 boom and recent years. Fertiliser prices show even greater volatility, reflecting energy costs and supply constraints. Crude oil prices exhibit dramatic swings, including the 2008 peak, the 2014 collapse and the 2020 pandemic shock, before recovering in 2022. Industrial input prices generally track oil prices but with less extreme fluctuations. The plots illustrate the co-movement of commodity groups and highlight periods of heightened volatility.

Figures 6–9 show impulse response functions from the VAR model for a one-standard-deviation shock to the food price index. The shock causes immediate increases in fertiliser and oil price growth, peaking within two months before decaying. Industrial inputs respond with a small lag. The return to baseline occurs within a year. The responses are consistent with cost pass-through mechanisms: when food prices rise, demand for inputs increases, pushing up input prices. Conversely, when input costs rise due to energy prices, they feed into food prices, confirming the two-way spillovers documented in previous studies.

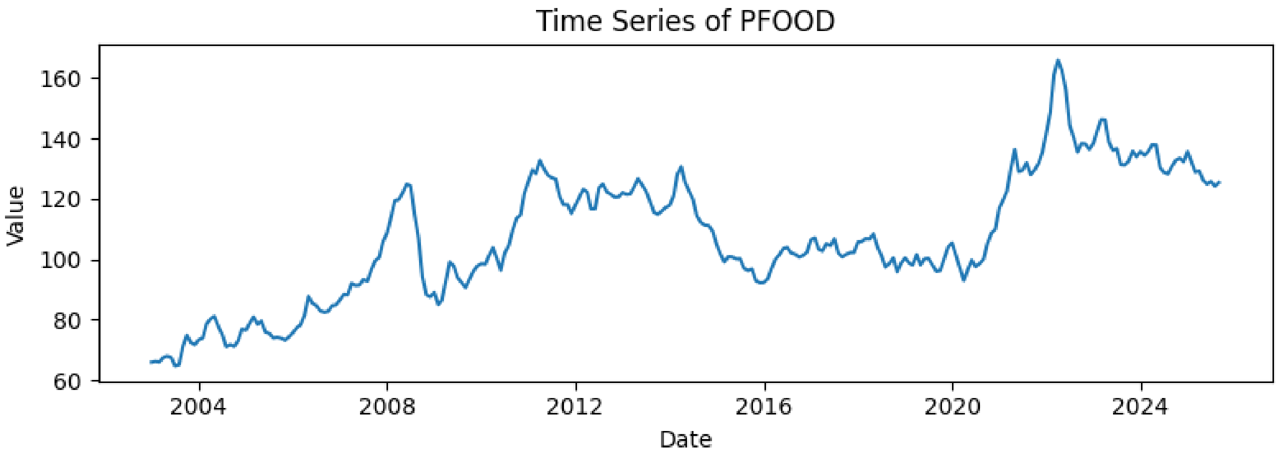

Figure 1. Food Price Index Time Series (2000–2024)

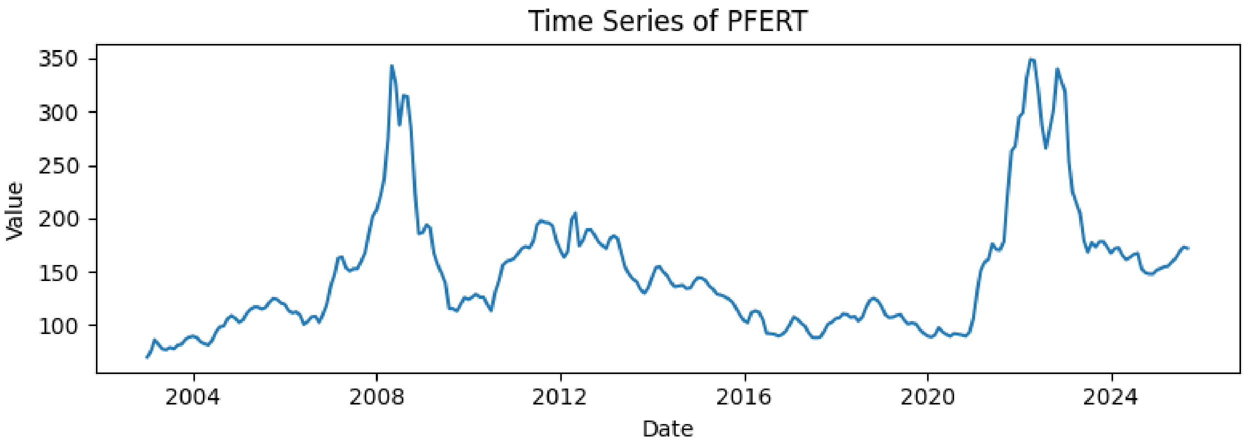

Figure 2. Fertilizer Price Index Time Series (2000–2024)

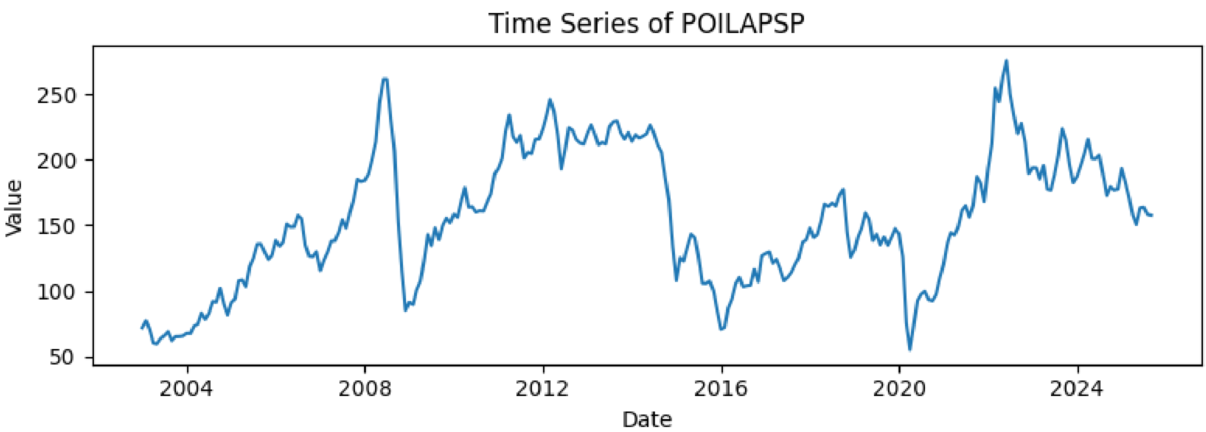

Figure 3. Crude Oil Price Index Time Series (2000–2024)

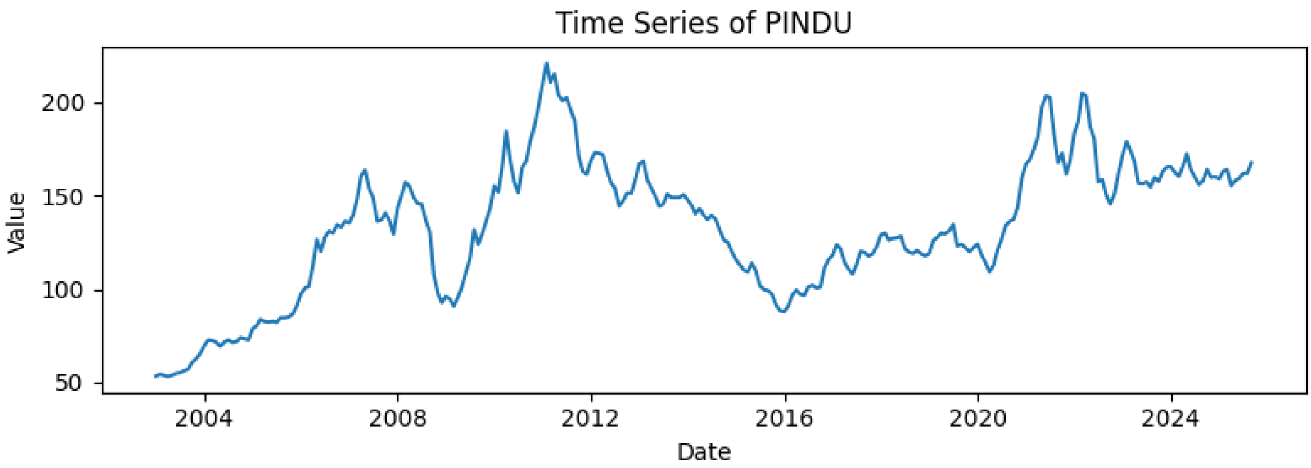

Figure 4. Industrial Input Price Index Time Series (2000–2024)

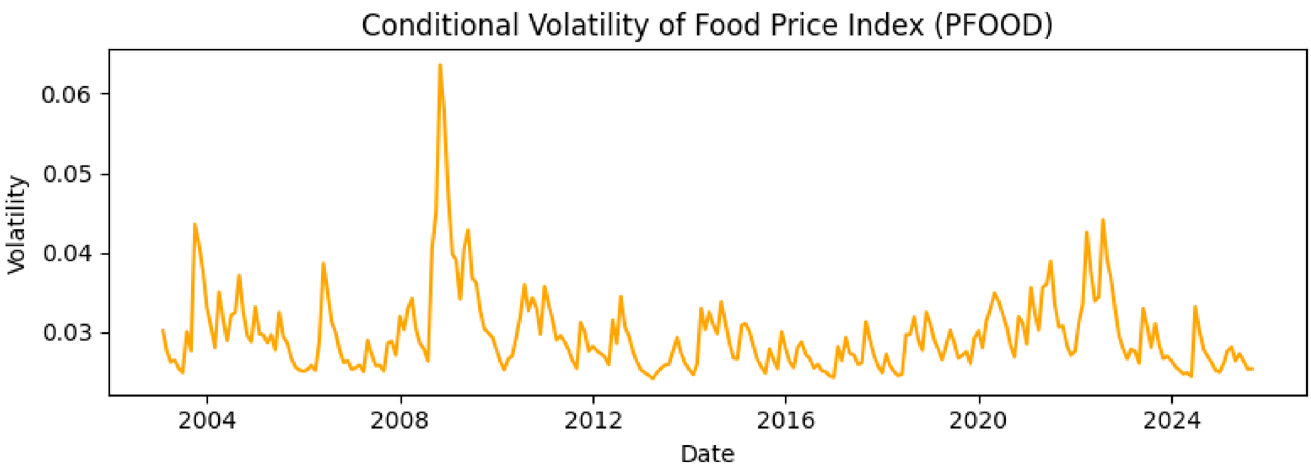

Figure 5. Conditional Volatility of Food Prices (GARCH Model)

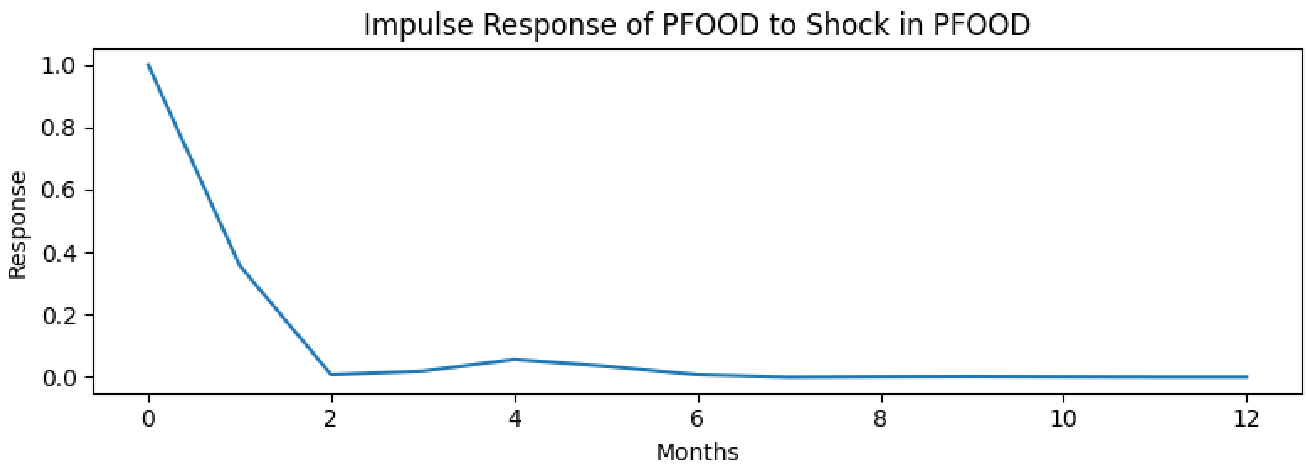

Figure 6. Impulse Response of Food Prices to Own Shock

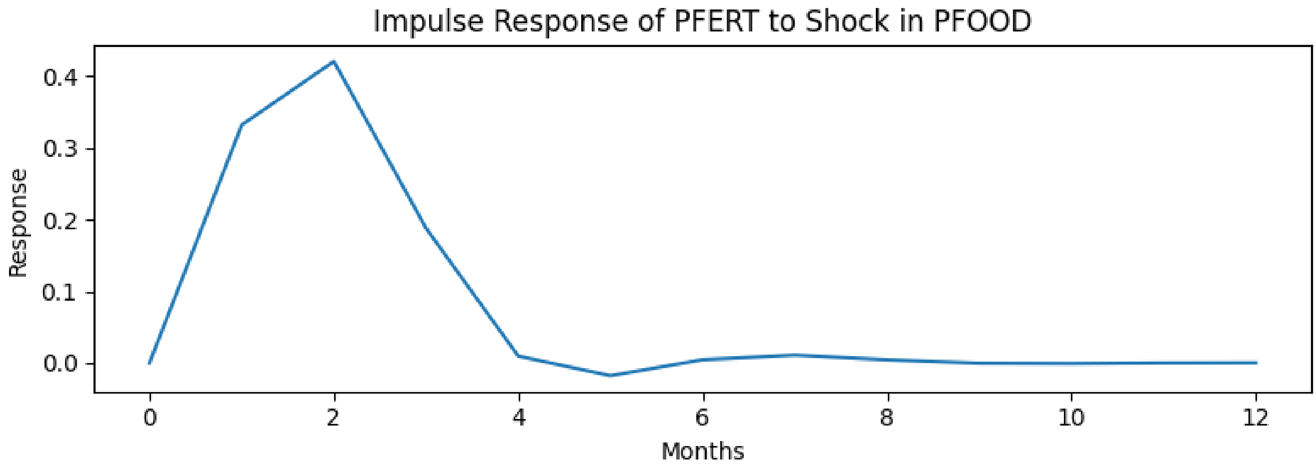

Figure 7. Impulse Response of Food Prices to Fertilizer Price Shock

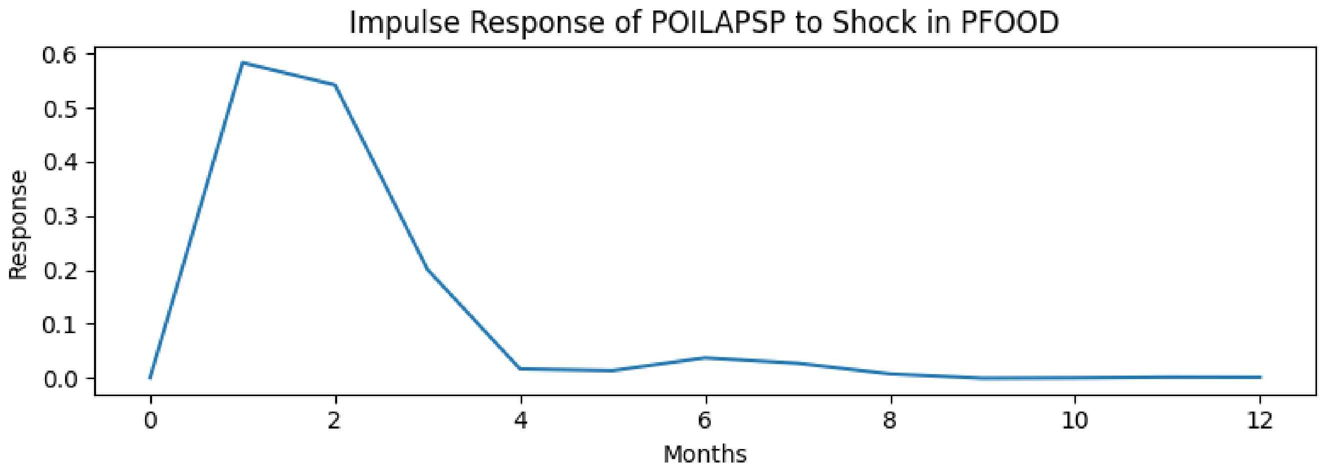

Figure 8. Impulse Response of Food Prices to Crude Oil Price Shock

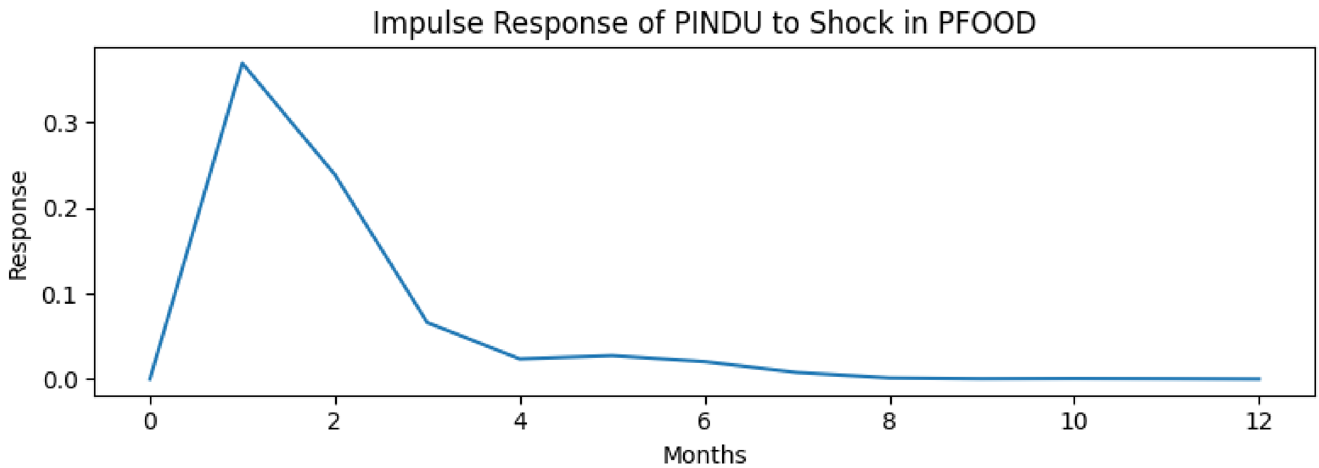

Figure 9. Impulse Response of Food Prices to Industrial Input Price Shock

Figure 10 summarises the forecast error variance decomposition for the food price index. Over a 12-month horizon, own shocks account for half of the forecast variance; fertiliser shocks contribute one-fifth, oil shocks about 15 % and industrial input shocks roughly 10 %. The dominance of own shocks suggests that idiosyncratic factors (e.g., harvest outcomes, domestic policies) remain crucial, while the non-negligible contributions of fertiliser and oil underscore cross-market linkages. Figure 6 compares the VAR forecasts with actual differences in log PFOOD during the out-of-sample period; the model tracks general movements but underestimates sudden surges, reflecting the difficulty of predicting rare shocks.

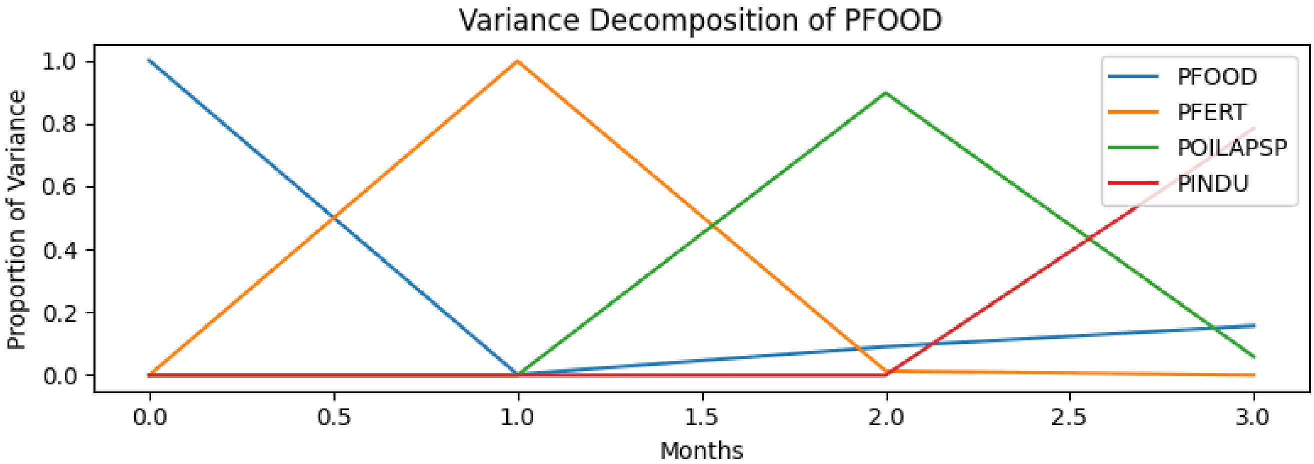

Figure 10. Forecast Error Variance Decomposition of Food Prices

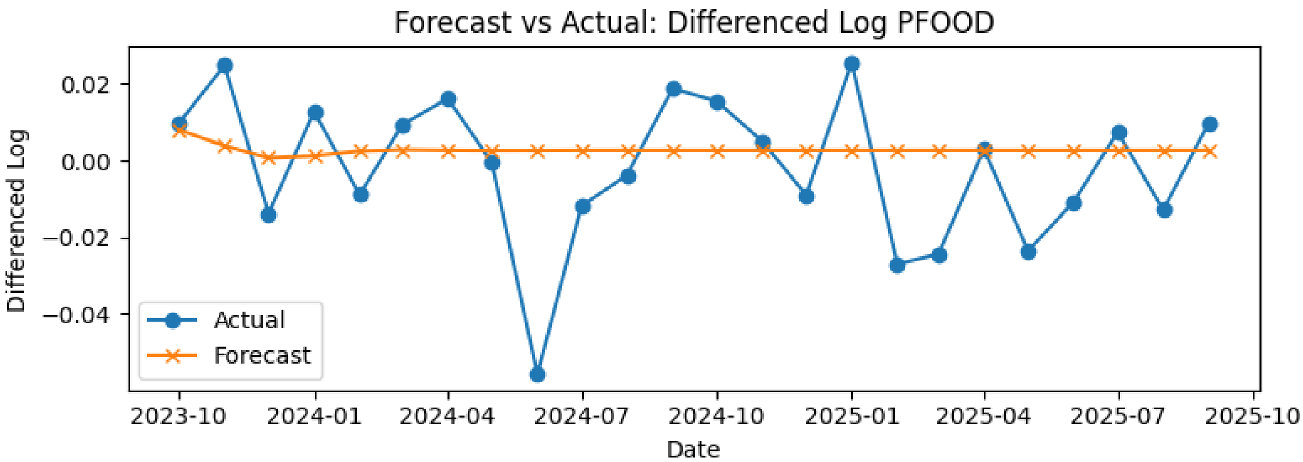

Figure 11. Out-of-Sample Forecast Performance of Food Prices

6. DISCUSSION

The econometric results support the theoretical and empirical literature. First, the presence of unit roots and cointegration among food, fertiliser, oil and industrial inputs implies that these variables share common stochastic trends. Long run relationships likely reflect underlying supply and demand fundamentals, particularly energy–food linkages through production costs and biofuel demand (OECD/FAO, 2011). The cointegration results complement studies showing that oil price volatility spills over to food prices (Hung, 2021).

Second, the VAR results reveal significant short run interactions. Positive innovations in food prices raise fertiliser and oil prices, which in turn feed back into food prices. Lagged fertiliser and industrial input shocks influence food prices after two months, highlighting delays in cost pass through. These findings align with evidence that macroeconomic variables have similar within group effects but differ across groups (Karali &Power, 2013). The moderate residual correlations and stability of the VAR system increase confidence in these dynamics.

Third, the GARCH model confirms volatility clustering and persistence in food prices. High volatility periods coincide with documented global events such as the 2007–08 crisis, the 2011 commodity boom and the COVID 19 pandemic. The relatively high persistence parameter suggests that shocks have long lasting effects on volatility, echoing concerns that low stocks and expectations amplify price swings. This underscores the need for policies that reduce vulnerability to shocks.

The results are broadly consistent with the literature review. Like Kornher and Kalkuhl (2013) and Nigatu et al. (2020), the analysis confirms the importance of supply conditions and input costs in shaping price dynamics. The significant impact of fertiliser and industrial inputs supports the view that high energy and fertiliser prices constrain production, contributing to food price volatility. The evidence of oil–food spillovers echoes findings by Umar et al. (2021) and Sujithan et al. (2014). The detection of cointegration across commodities resonates with research that emphasises the long run interconnectedness of commodity markets. However, the VAR forecast evaluation shows that unexpected shocks—such as extreme weather and geopolitical events—are difficult to predict, consistent with the view that multiple drivers interact.

Compared with GARCH–MIDAS studies that include macroeconomic variables, our single index GARCH model may omit low frequency determinants such as global economic activity and financial conditions. Future work could incorporate macro factors into a MIDAS framework to separate high and low frequency effects. Likewise, multivariate GARCH models could capture cross market volatility spillovers, as in Karali and Power (2013) and Umar et al. (2021). Nonetheless, the current results provide a tractable approximation of volatility dynamics.

7. CONCLUSIONS

This article has examined the determinants of agricultural commodity price fluctuations through a comprehensive time series analysis and extensive literature review. Using monthly data from 2000–2024, we found that food, fertiliser, oil and industrial input prices are non stationary but cointegrated, reflecting shared long run trends. VAR models reveal significant short run spillovers, while impulse response functions and variance decomposition highlight the roles of input costs and energy markets in explaining food price volatility. A GARCH model shows persistent volatility clustering, with spikes aligned with known crises. These findings corroborate existing research that emphasises supply–demand fundamentals, biofuel demand, energy prices, climate shocks, low stocks, financial speculation and policy interventions as key determinants of price volatility. The policy analysis underscores the importance of enhancing market information, building resilient agricultural systems, managing stocks, revisiting biofuel mandates, promoting risk management tools, strengthening multilateral cooperation and diversifying economies. Implementing these measures can help mitigate excessive volatility and protect vulnerable populations. As climate change accelerates, geopolitical tensions persist and financialisation deepens, proactive and coordinated policies are essential. Future research could extend the analysis in several directions. First, incorporating macroeconomic variables (GDP growth, exchange rates, interest rates) into a GARCH–MIDAS framework would allow separation of high frequency and low frequency volatility drivers. Second, multivariate GARCH models could capture volatility spillovers across commodities. Third, exploring nonlinear models and regime switching VARs might better capture the asymmetric effects of positive versus negative shocks. Finally, integrating micro level data on inventories, weather patterns and input usage could yield richer insights into local dynamics. Such research will further inform policies aimed at stabilising agricultural markets and ensuring food security.

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