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Macroeconomic Determinants of Long-Run Volatility in Indian Agricultural Commodity Futures: A GARCH-MIDAS Analysis

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Abstract

This study examines whether macroeconomic conditions explain the long-run volatility of selected agricultural commodity futures in India. Daily futures-price data for castor seed, mustard seed, soybean, maize and sugar are analysed from January 2010 to December 2021. The GARCH-MIDAS framework separates short-run volatility generated by daily market movements from long-run volatility associated with lower-frequency macroeconomic information. The explanatory variables comprise the Consumer Price Index, Industrial Production Index, short-term interest rate, stock-market index and exchange rate. The reported estimates indicate volatility persistence and show that macroeconomic effects are heterogeneous rather than uniform. Inflation is predominantly negatively associated with long-run volatility, whereas industrial production, interest rates, stock-market conditions and exchange-rate movements display commodity-specific effects. Castor seed is particularly responsive to exchange-rate and stock-market conditions; mustard seed and soybean show sensitivity to monetary and financial-market factors; and maize and sugar exhibit comparatively strong but directionally different responses to interest-rate, exchange-rate and industrial-production movements. These findings suggest that agricultural commodities should not be treated as a homogeneous asset class. Commodity-specific macroeconomic information can improve volatility assessment and support hedging, risk-management and policy decisions in India's agricultural futures market.

Keywords: Agricultural commodity futures; GARCH-MIDAS; long-run volatility; macroeconomic determinants; India

1. Introduction

Volatility in agricultural commodity prices has important consequences for producers, processors, traders, consumers and policymakers. Sudden and persistent price movements affect farm income, procurement costs, food-price inflation, inventory decisions and the effectiveness of futures-market hedging. These consequences are especially important in emerging economies such as India, where agricultural markets are exposed to production uncertainty, policy intervention, changing monetary conditions and fluctuations in domestic and international demand. Understanding the sources of agricultural futures volatility is therefore necessary for market-based risk management and public policy.

Agricultural commodity volatility may arise from production cycles, inventories, weather conditions and seasonal demand, but it can also be affected by broader economic conditions. Inflation changes input costs and expectations; industrial production reflects economic activity and commodity demand; interest rates influence inventory-holding costs and the relative attractiveness of financial and commodity assets; and exchange-rate movements alter the domestic prices of internationally traded commodities. Stock-market conditions can also transmit investor sentiment and financial liquidity to futures markets. International evidence confirms that commodity prices respond to macroeconomic activity and that agricultural markets are linked to exchange rates, crude oil and financial conditions (Alquist et al., 2020; Fernandez-Diaz & Morley, 2019; Yin & Han, 2016).

A central methodological issue is that futures prices and macroeconomic indicators are observed at different frequencies. Futures prices are available daily, whereas inflation, industrial production and other macroeconomic variables are generally reported monthly. Conventional GARCH models capture volatility clustering in daily returns but normally represent volatility through a single high-frequency process. They may therefore attribute slowly evolving macroeconomic effects to persistent short-run volatility. Evidence from spline-GARCH and related component models shows that allowing unconditional variance to change gradually improves model fit and provides a more realistic assessment of volatility persistence (Engle & Rangel, 2008; Karali & Power, 2013).

The GARCH-MIDAS framework addresses this issue by decomposing total volatility into short-run and long-run components. Its short-run component captures daily fluctuations and volatility clustering, while its long-run component can be linked to variables observed at a lower frequency. Engle et al. (2013) show that macroeconomic information, including inflation and industrial production, can explain long-term movements in financial-market volatility. The method preserves the information contained in daily returns without artificially converting monthly macroeconomic observations into daily data.

Previous studies establish that macroeconomic variables can influence commodity volatility, but their effects are not necessarily uniform. Karali and Power (2013) identify common and commodity-specific determinants of agricultural, energy and metal futures volatility. Mo et al. (2018) document a long-run volatility component in Chinese and Indian commodity futures and show that domestic and international macroeconomic information contributes to it. Futures markets also contain uneven predictive information across commodities and horizons (Chinn & Coibion, 2014). Macroeconomic and financial predictors have demonstrated forecasting value for commodity prices and volatility (Fang et al., 2018; Gargano & Timmermann, 2014), while economic and financial uncertainty comoves strongly with commodity-market volatility (Prokopczuk et al., 2019). However, agricultural commodities differ in production characteristics, storability, trade exposure, regulation and end use. Evidence from aggregate indices or mixed commodity samples may therefore conceal commodity-level differences.

This study examines the macroeconomic determinants of long-run volatility in five Indian agricultural commodity futures: castor seed, mustard seed, soybean, maize and sugar. It asks whether inflation, industrial production, short-term interest rates, stock-market conditions and exchange-rate movements explain long-run volatility and whether their effects differ across commodities. By estimating separate commodity-specific GARCH-MIDAS models, the study avoids treating agricultural futures as a homogeneous asset class and provides evidence relevant to hedgers, traders, exchanges and policymakers.

The remainder of the article develops the hypotheses and study model, describes the data and methodology, reports the empirical findings and concludes with implications and limitations.

2. Theoretical Background, Literature Review and Hypotheses

2.1 Inflation and economic activity

Commodity-futures prices reflect expectations concerning future supply, demand and the cost of holding commodities. Inflation can increase cultivation, processing, storage and transportation costs and alter expectations about future prices. Expected inflation may be incorporated gradually, whereas unexpected inflation can increase uncertainty about input costs, monetary-policy responses and future demand. Engle et al. (2013) demonstrate that inflation can explain long-run volatility, while Mo et al. (2018) show that low-frequency macroeconomic information contributes to commodity-futures volatility in India and China. Related evidence indicates that macroeconomic and policy uncertainty can materially affect agricultural and other commodity-market volatility (Bakas & Triantafyllou, 2018; Hu et al., 2020; Joëts et al., 2017). Because agricultural commodities differ in storability, regulation and trade exposure, the direction of the inflation effect may vary.

Industrial production represents economic activity and demand for agricultural inputs. Expansion can increase demand for edible oils, animal feed, textiles, biofuels and processed foods; if supply cannot adjust quickly, volatility may rise. Conversely, stable expansion can make demand more predictable. Karali and Power (2013) find that macroeconomic conditions explain slowly changing commodity volatility, although individual determinants differ across commodities. Global activity also contributes to commodity-price comovement (Alquist et al., 2020).

H1: The Consumer Price Index significantly influences the long-run volatility of Indian agricultural commodity futures.
H2: Industrial production significantly influences the long-run volatility of Indian agricultural commodity futures.

2.2 Interest rates and monetary conditions

Interest rates affect commodity markets through inventory costs, investment decisions and aggregate demand. Higher rates increase the opportunity cost of holding inventories, while lower rates reduce carrying costs and may increase the attractiveness of commodities relative to interest-bearing assets. Frankel (2008) argues that low real interest rates can raise real commodity prices through inventory and monetary-transmission channels. The volatility effect is theoretically ambiguous because rate changes can either stabilise prices by discouraging speculative demand or increase uncertainty through rapid adjustments in inventories and expectations.
H3: The short-term interest rate significantly influences the long-run volatility of Indian agricultural commodity futures.

2.3 Stock-market and exchange-rate conditions

The expansion of organised commodity derivatives has increased the potential for information and capital transmission between financial and commodity markets. Stock-market movements reflect investor sentiment, liquidity, risk appetite and expectations about economic activity. Portfolio rebalancing between equities and commodities can transmit volatility across markets. Andreasson et al. (2016) identify nonlinear linkages among commodity returns, stock-market dynamics, exchange rates and uncertainty. Batten et al. (2010), however, find that identical macroeconomic factors do not explain all precious-metal volatilities, illustrating the danger of treating commodities as a single asset class.

Exchange-rate movements change the domestic value of internationally traded commodities. Rupee depreciation can increase the cost of imported commodities and inputs while improving export competitiveness; appreciation can produce the reverse. The volatility response depends on whether a commodity is imported, exported or mainly consumed domestically. Exchange rates can also transmit global shocks into domestic futures markets. Hua (1998) identifies macroeconomic and monetary shocks as important influences on primary commodity prices.

H4: Stock-market conditions significantly influence the long-run volatility of Indian agricultural commodity futures.
H5: Exchange-rate movements significantly influence the long-run volatility of Indian agricultural commodity futures.

2.4 Research gap and model of the study

Existing research confirms that macroeconomic conditions can influence commodity volatility, but studies combining agricultural, energy and metal commodities may obscure differences within agriculture. In addition, single-frequency volatility models cannot directly integrate daily futures returns with monthly macroeconomic observations. Indian evidence shows that structural breaks and macroeconomic variables can alter agricultural price dynamics (Bodhanwala et al., 2020), while GARCH-MIDAS studies support the relevance of low-frequency information (Mo et al., 2018; Sreenu et al., 2021). Further commodity-specific analysis is justified because agricultural contracts differ in production cycles, storability, trade orientation and government intervention.

The study proposes that total conditional volatility consists of a short-run component driven by daily return shocks and previous volatility and a long-run component associated with monthly macroeconomic conditions. Separate models are estimated for each commodity-variable combination, allowing the sign and magnitude of the long-run effect to differ across castor seed, mustard seed, soybean, maize and sugar.

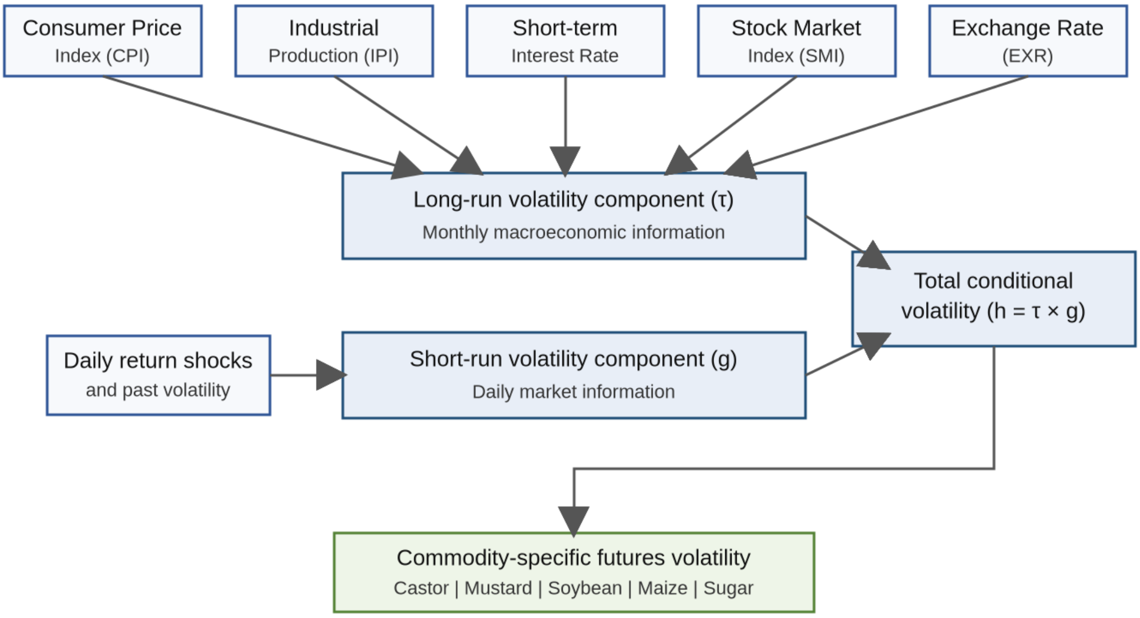

Figure 1. Conceptual model of the study

Total conditional volatility = Short-run volatility × Long-run volatility

$h_{i,t} = \tau_{i,m} \times g_{i,t}$ (1)

In Equation (1), $h_{i,t}$ denotes total conditional variance, $\tau_{i,m}$ denotes the long-run component during month m, and $g_{i,t}$ denotes short-run daily volatility.

3. Data and Methodology

3.1 Data and variables

The study uses daily closing futures prices for castor seed, mustard seed, soybean, maize and sugar from 1 January 2010 to 31 December 2021. Observations were compiled from the Multi Commodity Exchange of India, the National Commodity and Derivatives Exchange and the Centre for Monitoring Indian Economy, depending on contract availability. The selected commodities differ in production, storage, end use and trade exposure. Five monthly variables are examined: the Consumer Price Index (CPI), Industrial Production Index (IPI), short-term interest rate (STIR), stock-market index (SMI) and exchange rate (EXR). CPI represents inflation; IPI captures economic activity; STIR represents monetary conditions; SMI captures financial-market performance; and EXR reflects the external value of the Indian rupee.

$r_{i,t} = 100 \times [\ln(P_{i,t}) - \ln(P_{i,t-1})]$ (2)

Here, $r_{i,t}$ is the percentage logarithmic return of commodity i on trading day t, $P_{i,t}$ is its closing futures price, and $P_{i,t-1}$ is the price on the preceding trading day. Non-trading days are excluded and observations are arranged chronologically before returns are calculated.

3.2 Preliminary analysis

The analysis begins with mean, median, standard deviation, skewness, kurtosis and the Jarque-Bera statistic. Skewness measures asymmetry, while kurtosis indicates the frequency of extreme observations. The Jarque-Bera test evaluates normality. Stationarity and conditional heteroscedasticity should be assessed using the augmented Dickey-Fuller and ARCH-LM tests. Stationary returns and significant ARCH effects support the use of GARCH-based models.

3.3 GARCH-MIDAS specification

Following Engle et al. (2013), the return equation separates total conditional variance into long-run and short-run components:

$$r_{i,t} = \mu_i + \sqrt{(\tau_{i,m} \times g_{i,t})} \times \varepsilon_{i,t}, \qquad \varepsilon_{i,t} \sim N(0,1) \qquad (3)$$

Here, μ_i is the mean return, $g_{i,t}$ is short-run volatility, $\tau_{i,m}$ is long-run volatility, and $\varepsilon_{i,t}$ is the standardised error term. The short-run component follows a GARCH(1,1) process:

$$g_{i,t} = (1 - \alpha_i - \beta_i) + \alpha_i[(r_{i,t-1} - \mu_i)^2 \div \tau_{i,m}] + \beta_i g_{i,t-1} \qquad (4)$$

The parameter α_i measures the response to recent return shocks and β_i measures volatility persistence. Positivity and mean reversion require $\alpha_i > 0$, $\beta_i > 0$ and $\alpha_i + \beta_i < 1$. The long-run component is linked to monthly macroeconomic information as follows:

$$\ln(\tau_{i,m}) = m_{0,i} + \theta_{i,j} \Sigma_{k=1}^{K} [\varphi_k(\omega_1,\omega_2) \times X_{j,m-k}] \qquad (5)$$

In Equation (5), $m_{0,i}$ is the long-run constant, $\theta_{i,j}$ measures the effect of macroeconomic variable j on commodity i, K is the number of monthly lags, $X_{j,m-k}$ is a lagged macroeconomic observation, and φ_k is its normalised MIDAS weight. The Beta weighting function is specified as:

$$\varphi_k(\omega_1,\omega_2) = [(k/K)\text{^}(\omega_1-1)(1-k/K)\text{^}(\omega_2-1)] \div \Sigma_{j=1}^{K}[(j/K)\text{^}(\omega_1-1)(1-j/K)\text{^}(\omega_2-1)] \qquad (6)$$

The coefficient $\theta_{i,j}$ is the principal parameter: a positive value associates the variable with higher long-run volatility, while a negative value indicates a volatility-reducing association. A realised-variance model is estimated as a benchmark, after which CPI, IPI, STIR, SMI and EXR are introduced separately. Parameters are estimated by maximum likelihood, and the Bayesian Information Criterion is used to compare specifications.

4. Empirical Results and Discussion

4.1 Distributional characteristics and short-run persistence

The reported descriptive results show that the five commodity-return series differ in central tendency, dispersion and distributional shape. Negative skewness is reported for castor seed, mustard seed and sugar, whereas soybean and maize are positively skewed. Kurtosis exceeds the normal-distribution benchmark for every commodity, indicating fat tails and relatively frequent extreme returns. The reported Jarque-Bera statistics further suggest departures from normality. These features support the use of conditional-volatility models.

Table 1. Reported short-run GARCH parameters and persistence

Commodity	α	β	α + β	Assessment
Castor seed	0.3853	0.3721	0.7574	Mean reverting
Mustard seed	0.9428	0.4186	1.3614	Requires verification

Commodity	α	β	α + β	Assessment
Soybean	0.0494	0.0592	0.1086	Mean reverting
Maize	0.5932	0.7252	1.3184	Requires verification
Sugar	0.7372	0.4726	1.2098	Requires verification

Note: Values are reproduced from the original estimation table. The condition $\alpha + \beta < 1$ is required for conventional mean reversion.

Table 1 indicates that past shocks and previous volatility contribute to short-run dynamics, but the estimated persistence varies considerably. Castor seed and soybean satisfy the conventional mean-reversion condition. The reported sums for mustard seed, maize and sugar exceed unity, implying a non-stationary short-run variance if the coefficients have been transcribed correctly. Those specifications require verification against the original output or re-estimation before formal hypothesis decisions are made.

4.2 Macroeconomic determinants of long-run volatility

Table 2. Reported macroeconomic coefficients in the long-run volatility component

Commodity	CPI	IPI	STIR	SMI	EXR
Castor seed	−0.5821	0.6948	0.0937	1.4902	−3.0890
Mustard seed	−0.5830	0.5930	−0.0190	−2.0520	0.5903
Soybean	−0.3854	−0.2580	−0.5450	−1.5940	0.0092
Maize	0.0582	0.0096	−1.5300	0.5029	−2.0050
Sugar	−0.2784	−0.0710	1.7946	−3.0020	−1.3000

Notes: CPI = Consumer Price Index; IPI = Industrial Production Index; STIR = short-term interest rate; SMI = stock-market index; EXR = exchange rate. Coefficients are reproduced from the original article; inconsistent reported p-values prevent reliable reassignment of significance levels.

The principal pattern in Table 2 is heterogeneity rather than a uniform macroeconomic response. CPI has a negative coefficient for castor seed, mustard seed, soybean and sugar but a small positive coefficient for maize. The results therefore do not support the general claim that inflation uniformly increases agricultural futures volatility. A possible interpretation is that predictable inflation is gradually incorporated into prices, while commodity-specific supply information generates greater short-run uncertainty; this interpretation remains conditional on verification of the CPI transformation and significance levels.

Industrial production is positively associated with the long-run volatility of castor seed, mustard seed and maize but negatively associated with soybean and sugar. The stronger positive values for castor seed and mustard seed may reflect their sensitivity to industrial and processing demand. The near-zero maize coefficient indicates a limited association in the reported model. These differences support the view that macroeconomic activity affects commodities according to their end uses and supply responsiveness (Karali & Power, 2013).

Interest-rate coefficients are negative for mustard seed, soybean and maize but positive for castor seed and sugar. The relatively large negative maize coefficient suggests that tighter monetary conditions may be associated with reduced inventory demand or speculative participation, whereas sugar exhibits the opposite response. Stock-market coefficients are positive for castor seed and maize and negative for mustard seed, soybean and sugar. The large magnitudes reported for castor seed, mustard seed and sugar imply potentially important financial-market transmission, but the opposite signs again reject a common response across agricultural contracts.

Exchange-rate coefficients are negative for castor seed, maize and sugar and positive for mustard seed and soybean. Castor seed reports the largest negative value, followed by maize and sugar. Variations in import dependence, export exposure and internationally priced inputs may explain these differences. The precise economic interpretation nevertheless depends on whether an increase in the exchange-rate series represents rupee depreciation or appreciation, which must be stated explicitly in the final data description.

4.3 Hypothesis assessment and overall discussion

The reported coefficient patterns are broadly consistent with the proposition that monthly macroeconomic information contributes to long-run agricultural futures volatility, as found by Mo et al. (2018) and Sreenu et al. (2021). However, the original significance stars and p-values conflict in several cells. Accordingly, H1-H5 can be evaluated conclusively only after the estimation output is verified. Directionally, the findings show that no macroeconomic variable has the same effect across all five commodities. The defensible substantive conclusion is therefore commodity-specific heterogeneity, not a uniformly positive macroeconomic influence.

The results have practical relevance. Hedgers and traders should monitor the macroeconomic indicators most closely associated with the particular commodity rather than rely on an aggregate agricultural-market signal. Exchanges may also consider commodity-specific responses when reviewing margin requirements and risk controls. Policy interpretation must remain cautious because the reported associations are not causal and because the stability and significance inconsistencies require correction before publication. Nevertheless, separating daily market volatility from slowly evolving macroeconomic volatility provides a useful framework for understanding risk in Indian agricultural futures markets.

5. Conclusion and Implications

5.1 Conclusion

This study examined whether monthly macroeconomic conditions explain the long-run volatility of castor seed, mustard seed, soybean, maize and sugar futures in India during 2010-2021. The GARCH-MIDAS framework was employed to separate short-run volatility arising from daily return shocks from long-run volatility associated with inflation, industrial production, short-term interest rates, stock-market conditions and exchange-rate movements. This mixed-frequency approach is appropriate because it retains daily market information while allowing gradually changing macroeconomic conditions to influence the long-run variance.

The reported results show that the selected agricultural commodities do not respond uniformly to macroeconomic information. CPI is negatively associated with long-run volatility for four of the five commodities, while industrial production produces positive effects for castor seed, mustard seed and maize and negative effects for soybean and sugar. Interest-rate, stock-market and exchange-rate coefficients also vary in sign and magnitude. Castor seed displays particularly large reported responses to stock-market and exchange-rate conditions; mustard seed and soybean are sensitive to financial and monetary factors; and maize and sugar show comparatively strong but directionally different responses to interest rates, industrial production and exchange-rate movements. The main conclusion is therefore not that macroeconomic variables uniformly increase volatility, but that their influence is commodity-specific.

5.2 Practical and policy implications

The findings have implications for several market participants. Hedgers should incorporate the macroeconomic indicators most relevant to the specific commodity when selecting hedge ratios, contract maturities and the timing of futures positions. Traders and portfolio managers may use the long-run volatility component as an additional risk signal when allocating capital across agricultural contracts. Commodity exchanges and clearing institutions can consider commodity-specific macroeconomic sensitivity when reviewing margin requirements, position limits and market-surveillance procedures. Policymakers should recognise that changes in interest rates, exchange rates and inflation conditions may not transmit uniformly across agricultural markets. A policy action that reduces volatility in one commodity may coincide with higher volatility in another because of differences in trade exposure, inventories, processing demand and market participation.

5.3 Limitations and future research

The study has several limitations. First, it considers five commodities and five domestic macroeconomic indicators, so the findings should not be generalised to the entire Indian agricultural futures market. Second, separate univariate models do not capture possible interactions or volatility spillovers among commodities. Third, the analysis does not explicitly control for rainfall, production shocks, inventories, crude-oil prices, global food prices, policy uncertainty or changes in trading regulation. Fourth, futures-series construction, contract rollover and the treatment of missing observations must be reported more fully. Finally, the reported significance levels and the short-run stability condition require verification against the original estimation output before journal submission.

Future research can extend the analysis to a broader set of agricultural contracts, incorporate domestic and global uncertainty indicators, and compare pre-crisis, crisis and post-crisis periods. Multivariate GARCH-MIDAS, regime-switching or structural-break models could reveal whether volatility transmission changes during exceptional market conditions. Out-of-sample forecasting comparisons using loss functions such as QLIKE and mean squared error would also determine whether macroeconomic information improves practical volatility prediction beyond a conventional GARCH benchmark.

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