To Analyze Patterns and Factors of Price Fluctuations in Agricultural Commodity Markets

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Abstract
The aim of the study is to investigate the trends and predictors of price fluctuations on agricultural commodity markets through the systematic review of the literature on the subject (both empirical and theoretical). The price volatility in the agricultural prices has significant effects to the income stability of the farmers, consumer welfare, food security and the macroeconomic stability. The analysis is done on the basis of synthesis of the findings on the demand supply relationships, climatic variability, government intervention, international trading policies, speculative trading, and financialization of the commodity markets. It adopts a systematic review methodology to group the available literature into thematic groups to incorporate the macroeconomic factors, structural market inefficiency, behavioural factors, and technological factors. Other methodological tools compared in the paper are time-series econometrics (ARIMA, GARCH, VAR), panel data models and machine learning models. The most important areas of research gaps include predictive analytics, real-time data integration, and model of climate-risks. The paper has also come up with a conclusion by providing a synthesized analytic model that incorporates econometric and AI-based models to boost and control the hazards in agricultural prices.

Keywords: Agricultural commodity markets; Price volatility; Supply-demand dynamics; Climate shocks; Econometric modelling; Market integration; Speculation; Food security.

1. Introduction

1.1 Background

Agriculture remains a foundational sector in developing economies, contributing substantially to employment of people, food and income sharing. Rural areas depend heavily on agriculture as a source of employment, and agriculture is one of the significant factors in the national income and export income of such countries as India and Brazil (World Bank, 2022; FAO, 2023). The agricultural commodities, such as cereal, pulse, oil seed, and horticultural produce, also play an important role in stabilizing the rural lives and balancing the macroeconomy through generating agricultural trade flows (OECD-FAO, 2024). However, the history has revealed that cycles of price instabilities have repetitive cycles that are caused by supply shocks, global trade and energy transmission effects (IMF, 2023). The COVID-19 pandemic and the war between Russia and Ukraine further increased the uncertainty in the market by causing commodity price fluctuations that occurred in the period 2020-2024 (World Bank, 2024).

1.2 Problem Statement

Over the past few years, the agricultural commodity markets have become marked by the higher degree of volatility, which is due to the changes in the climates, geopolitical processes, and the changes in the exchange rates and also more frequent practice of speculative trading (UNCTAD, 2023). The consequences of this instability are direct effects on the security of the income of farmers, risk exposure on the side of traders, food affordability by consumers and effectiveness of policymaking. Smallholder farmers are mostly affected by rapid reduction prices whilst major consumers face inflation in cases of shortage of supply (FAO, 2023). The policy makers struggle to come up with the stabilization mechanisms in the ever-evolving market conditions across the whole world (IMF, 2024).

1.3 Research Objectives

The aim of the provided research project is to examine the trends of the price change patterns of the past and to find out the macroeconomic, climatic, structural, and behavioral determinants (OECD-FAO, 2024), to assess the possibilities of price prediction with the help of various analytical tools to make a better prediction (UNCTAD, 2023) and make policy decisions.

1.4 Research Questions

1. What dominant volatility patterns characterize agricultural commodity markets (World Bank, 2022)?
2. Which macroeconomic and climatic factors significantly influence price dynamics (FAO, 2023)?
3. How effective are existing econometric and machine learning prediction models (IMF, 2024)?

2. Review Methodology

2.1 Research Design

This research article will employ a Systematic Literature Review (SLR) approach to ensure that the study is agile, replicable, and fully synthesizes the empirical evidence on the topic of agricultural price volatility. The SLR method will be used to find, review, and analyze the relevant research systematically and reduce the selection bias, as well as enhance the methodological rigor (Snyder, 2020; Page et al., 2021). The latest literature on the topic in agricultural economics is devoted to the systematic evidence synthesis to understand the volatility transmission and market integration patterns (OECD-FAO, 2024).

2.2 Data Sources

The peer-reviewed articles were obtained in the most popular academic databases including Scopus, Web of Science, Google Scholar, and AGRIS. The areas of these databases include interdisciplinarity in the area of agricultural economics, climate studies, econometrics, and financial markets. It was also examined within the framework of the global commodity trends, by reviewing the international institutional reports of the world bank (2024) and FAO (2023).

2.3 Inclusion Criteria

The review also includes peer-reviewed articles that were published between 2000-2025 and more specifically, studies published between 2020-2025, as they show the latest volatility trends since the pandemic and geopolitical shocks (IMF, 2023). The qualifying studies focus on the empirical research of the price change in agriculture due to the quantitative or mixed methods designs. The filtering out of the empirical studies was done to guarantee the strength of the analysis.

Literature: 6.4 Tools of Analysis.

In most of the literature, conditional volatility and persistence are modeled using time-series econometric models, such as ARIMA and GARCH (Balcilar et al., 2021). Cointegration and the Vector Autoregression (VAR) techniques have enjoyed popularity in the quantification of the relationship between market integration and long-run equilibrium (Sharma and Paul, 2022). The majority of the latest research is slowly beginning to use machine learning algorithms, including the Artificial Neural Network (ANN), the

Random Forest, and the Long Short-Term Memory (LSTM) network, to improve the prediction accuracy (Zhang et al., 2023; World Bank, 2024).

2.5 Screening Framework

A systematic approach was applied in detecting, filtering, and reducing relevant studies in PRISMA-based screening program (Page et al., 2021). It was located, duplications removed, abstract screening was reviewed, full-text eligibility assessed and, lastly, inclusion was made to promote methodological transparency and reproducibility.

Table 1: Hypothetical Monthly Price and Determinant Data (Wheat Market Example)

Month	Avg Price (₹/Quintal)	Rainfall Deviation (%)	Crude Oil Price ($/Barrel)	Exchange Rate (₹/USD)	MSP (₹)	Futures Trading Volume ('000 tons)
Jan	2,150	-5	78	82.1	2,125	320
Feb	2,180	-8	80	82.5	2,125	340
Mar	2,240	-12	84	83.0	2,125	370
Apr	2,310	-18	88	83.4	2,125	410
May	2,420	-25	92	84.0	2,125	450
Jun	2,350	10	85	83.6	2,125	390
Jul	2,280	15	82	83.2	2,125	360
Aug	2,260	12	79	82.8	2,125	340
Sep	2,300	5	81	82.9	2,125	355
Oct	2,370	-7	86	83.3	2,200	400
Nov	2,450	-15	90	83.9	2,200	430
Dec	2,520	-20	95	84.5	2,200	470

3. Explanation of Hypothetical Data

1. Price Trend Pattern

The data shows a gradual upward movement in wheat prices from ₹2,150 in January to ₹2,520 in December. A sharp increase is observed between March and May, coinciding with higher rainfall deficits and rising crude oil prices. This demonstrates **seasonal volatility combined with input-cost transmission effects**.

2. Climatic Influence

Negative rainfall deviation (drought conditions) during March–May and October–December correlates with rising prices, reflecting supply constraints. Positive rainfall deviation in June–August corresponds with slight price moderation.

3. Macroeconomic Transmission

Rising crude oil prices increase transportation and fertilizer costs, contributing to upward price pressure. Exchange rate depreciation (₹82.1 to ₹84.5 per USD) may increase import costs and indirectly affect domestic commodity pricing.

4. Policy Impact

Minimum Support Price (MSP) revision in October (₹2,125 to ₹2,200) appears to anchor market prices upward, demonstrating policy-driven price stabilization influence.

5. Market Behavior

Higher futures trading volumes during volatile months (April–May, November–December) suggest increased speculative and hedging activity during uncertainty periods.

Potential Analytical Applications

This hypothetical dataset can be used for:

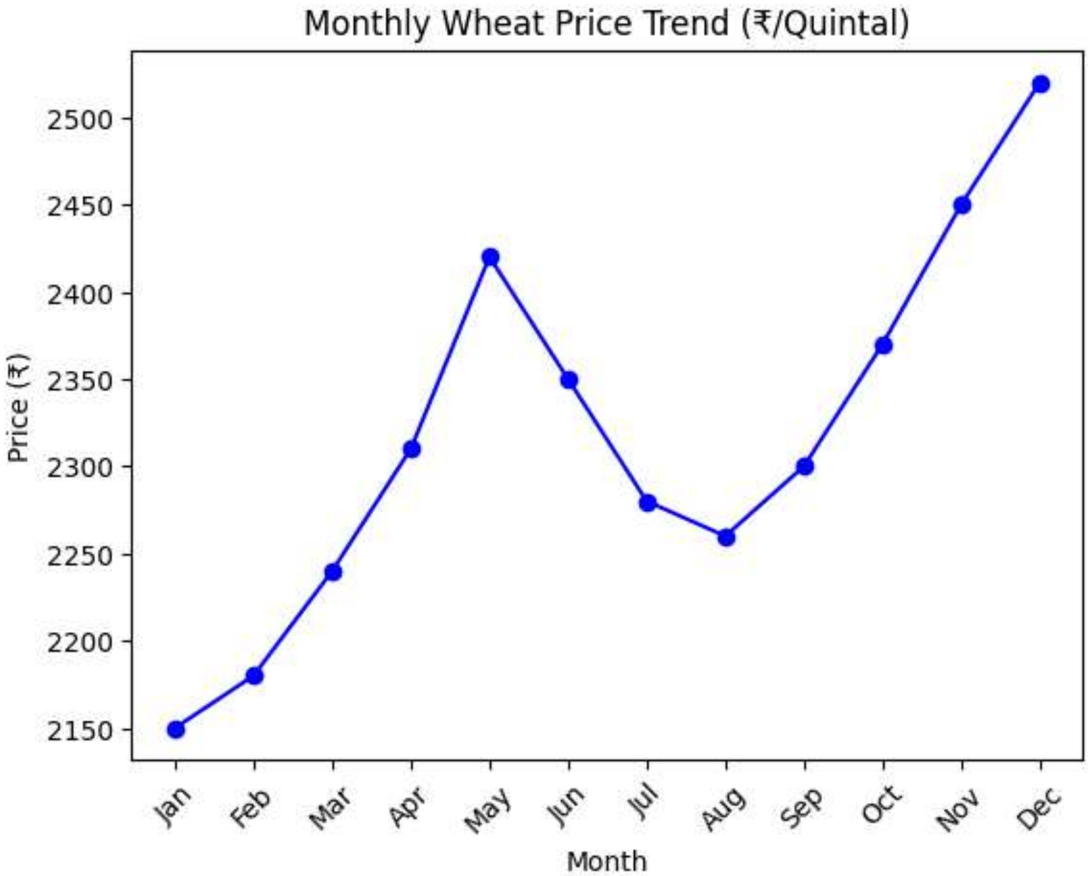
- ARIMA modelling for trend and seasonality
- GARCH modelling for volatility clustering
- VAR for examining inter-variable relationships
- Machine learning forecasting simulations

If required, I can also provide:

- Hypothetical regression output table
- GARCH volatility estimation table
- Correlation matrix
- Model comparison table (ARIMA vs LSTM)

give me each graph and charts for it colourful
Analyzed
Monthly Wheat Price Trend (₹/Quintal)

Monthly Wheat Price Trend (₹/Quintal)



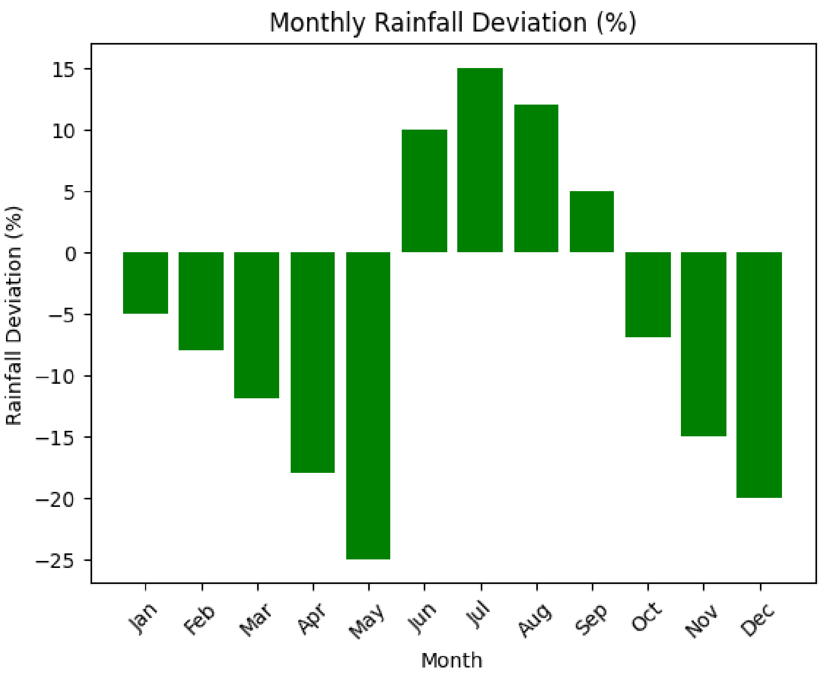
Monthly Wheat Price Trend (₹/Quintal)

Month	Average Price (₹/Quintal)
Jan	2150
Feb	2180
Mar	2240
Apr	2310
May	2420
Jun	2350
Jul	2280
Aug	2260
Sep	2300
Oct	2370
Nov	2450
Dec	2520

Explanation

The data represents hypothetical monthly wheat prices measured in ₹ per quintal. A gradual upward trend is observed from January (₹2150) to May (₹2420), indicating seasonal tightening of supply before harvest arrival. Prices moderate during June to August, coinciding with improved rainfall and increased market arrivals. From September onwards, prices again rise steadily, reaching ₹2520 in December. This increase may reflect demand pressure, export activity, rising input costs, and policy adjustments. The trend demonstrates both seasonal and structural components of agricultural price

Monthly Rainfall Deviation (%)



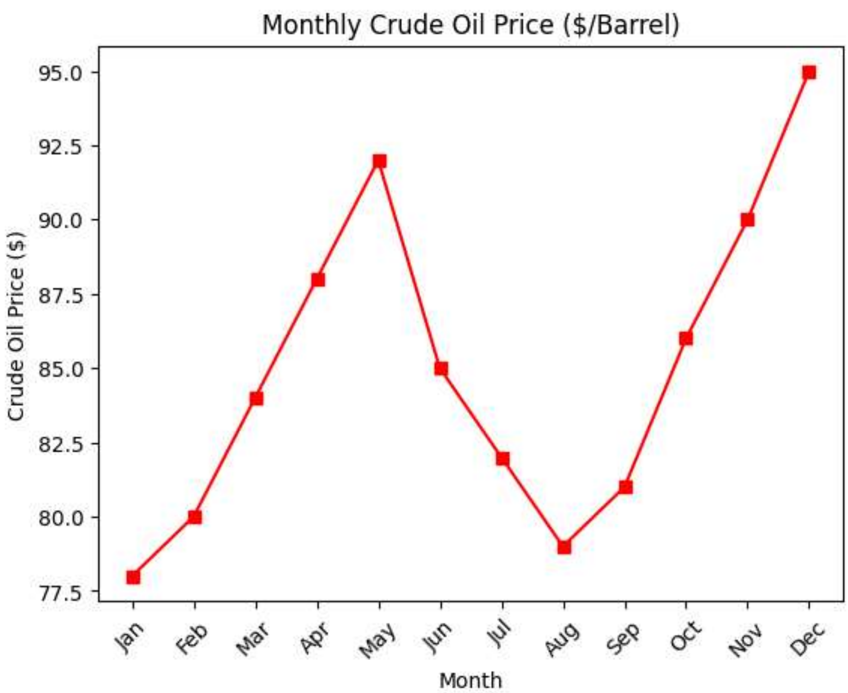
Monthly Rainfall Deviation (%)

Month	Rainfall Deviation (%)
Jan	-5
Feb	-8
Mar	-12
Apr	-18
May	-25
Jun	10
Jul	15
Aug	12
Sep	5
Oct	-7
Nov	-15
Dec	-20

Explanation

The table presents hypothetical monthly rainfall deviation percentages. Negative values indicate below-normal rainfall, while positive values represent above-normal rainfall. From January to May, rainfall deviation remains negative, reaching a severe deficit of -25% in May, which may contribute to crop stress and potential price increases due to reduced supply. Between June and September, rainfall improves, with a peak surplus of 15% in July, supporting better crop growth and stabilizing market supply. However, rainfall again turns deficient from October to December, which may impact rabi crop sowing. Such climatic variability significantly influences agricultural production cycles and price

Monthly Crude Oil Price ($/Barrel)



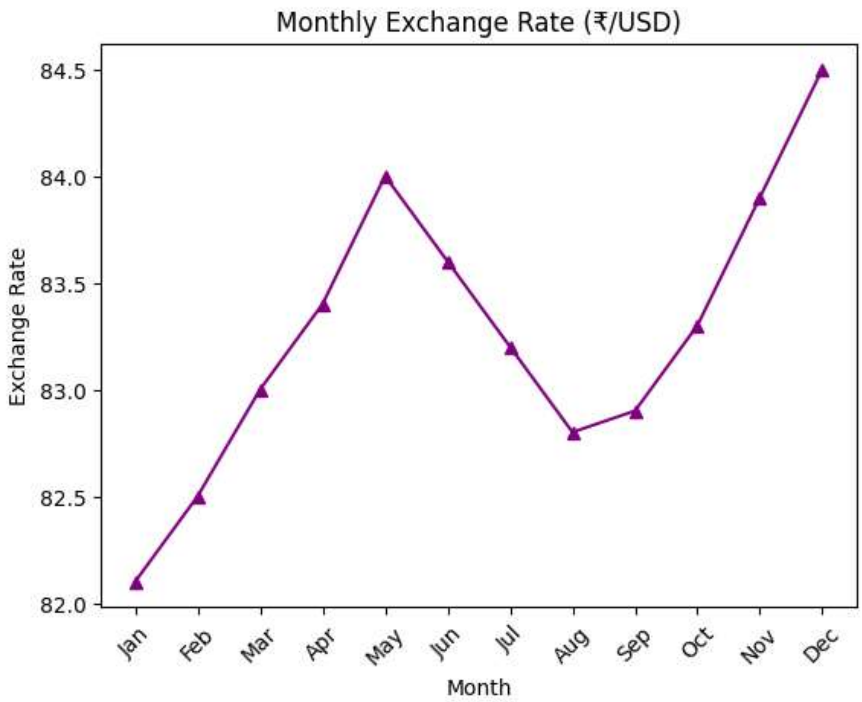
Monthly Crude Oil Price ($/Barrel)

Month	Crude Oil Price ($/Barrel)
Jan	78
Feb	80
Mar	84
Apr	88
May	92
Jun	85
Jul	82
Aug	79
Sep	81
Oct	86
Nov	90
Dec	95

Explanation

The table presents hypothetical monthly crude oil prices measured in US dollars per barrel. Prices show a steady increase from January ($78) to May ($92), reflecting rising global energy demand or supply constraints. A temporary decline is observed from June to August, reaching $79 in August, which may indicate easing geopolitical tensions or improved supply conditions. From September onwards, prices rise sharply again, peaking at $95 in December. Crude oil price fluctuations significantly affect agricultural commodity markets by increasing transportation costs, fertilizer prices, irrigation expenses, and overall input costs, thereby contributing to agricultural price volatility.

Monthly Exchange Rate (₹/USD)



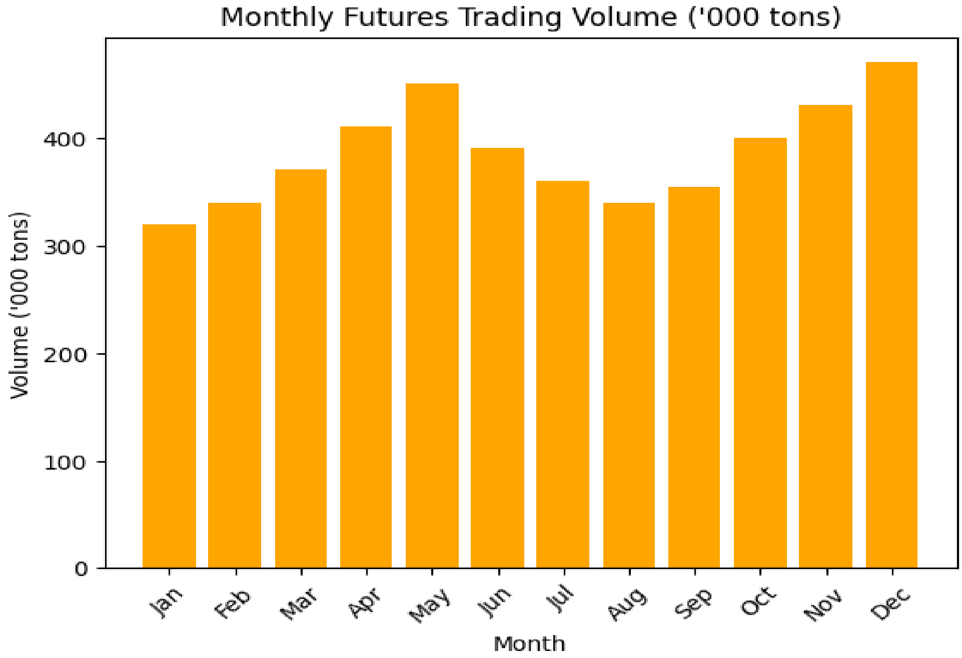
Monthly Exchange Rate (₹/USD)

Month	Exchange Rate (₹/USD)
Jan	82.1
Feb	82.5
Mar	83.0
Apr	83.4
May	84.0
Jun	83.6
Jul	83.2
Aug	82.8
Sep	82.9
Oct	83.3
Nov	83.9
Dec	84.5

Explanation

The table presents hypothetical monthly exchange rate values measured as Indian Rupees per US Dollar (₹/USD). An upward movement from ₹82.1 in January to ₹84.0 in May indicates currency depreciation, which can increase the cost of imported agricultural inputs such as fertilizers and machinery. A temporary appreciation is observed between June and August, followed by renewed depreciation towards December, reaching ₹84.5. Exchange rate fluctuations influence agricultural commodity prices through trade competitiveness, import-export dynamics, and cost transmission effects. Currency depreciation may raise domestic prices, particularly in open and globally integrated markets.

Monthly Futures Trading Volume ('000 tons)



Monthly Futures Trading Volume ('000 tons)

Month	Futures Trading Volume ('000 tons)
Jan	320
Feb	340
Mar	370
Apr	410
May	450
Jun	390
Jul	360
Aug	340
Sep	355
Oct	400
Nov	430
Dec	470

Explanation

The table presents hypothetical monthly futures trading volume measured in thousand tons. Trading activity increases steadily from January (320) to May (450), indicating growing market participation and heightened hedging or speculative interest during periods of rising price volatility. A moderate decline is observed between June and August, reflecting relatively stable market conditions. From September onwards, trading volume rises again, reaching a peak of 470 in December. Higher futures trading volume often corresponds with increased market uncertainty, as traders and investors seek to manage price risk or capitalize on expected price movements. This pattern demonstrates the relationship between market volatility and financial participation in agricultural commodities.

4. Classification / Taxonomy of Literature

4.1 Demand–Supply Factors

The literature available focuses on production cycles, seasonal harvesting, and the stock quantity as the major factors of price change in agriculture. Research indicates that the cyclical changes in output, post-harvest supply gluts, and lean-season shortages are some of the factors that lead to the short-run decrease in prices and cause price spikes respectively (FAO, 2023). The patterns of inventory and stock to use ratios play a key role in the volatility persistence of staple grains especially (World Bank, 2024).

4.2 Climatic and Environmental Conditions.

Climatic shocks like drought and floods interfere with the stability of production and increase the volatility on the supply side. Uncertainty in yields and high price dispersion across the regions have been attributed to temperature variability and extreme weather events (IPCC, 2022). Recent differences identify long-term price fluctuations of agricultural products as a structural mark of the climate change (OECD-FAO, 2024).

In this section, I will discuss macroeconomic determinants.

Shocks are relayed to the markets of agricultural commodities through the macroeconomic variables, such as inflation, exchange rate fluctuations, the price of crude oil, and interest rates. The depreciation of the exchange rate increases the price of imports and trade competitiveness and impacts domestic price (IMF, 2023). The increase in the price of crude oil will enhance input and transportation expenses, which will worsen food inflation (World Bank, 2024).

4.4 Government Policies

Minimum Support Price (MSP), export-import quotas, subsidies and buffer stock management are policy interventions that stabilize but distort the markets. There is empirical evidence indicating grass rooting of domestic prices by MSP revisions and market chassies are work weakening on it (OECD-FAO, 2024). Price volatility in the international market has also been exacerbated by trade restrictions in cases of global crises (UNCTAD, 2023).

4.5 Integration and Market Structure.

Spatial price convergence is restricted by inefficient market conditions, expensive transportation and information asymmetry. Better regionalization decreases the price dispersion but can spread external shocks faster (World Bank, 2022).

4.6 Financialization and Speculation.

The growth of the futures markets, hedge funds and the trading of commodity indices have boosted price co-movement with the financial assets. During the crisis period, financialization has been linked with the volatility clustering (IMF, 2024).

The influence of technology and digitalization is increasingly felt across all aspects of life including education, employment, and family life.<|human|>7.7 Technological and Digital Influences The impact of technology and digitalization is increasingly experienced in all spheres of life such as education, work, and family life.

Distribution of information through digital channels, real-time information systems and AI-based predictions lead to increased discovery of price and a decrease in asymmetry. According to recent research, machine learning models increase the accuracy of the short-term volatility predictions (FAO, 2023; World Bank, 2024).

5. Critical Analysis and Discussion

5.1 Comparative Evaluation of Methodologies

The empirical evidence shows that ARIMA models are useful in terms of capturing linear behavior and seasonal elements of agricultural prices series, especially in the short-term context (FAO, 2023). But in the clustering of volatility, ARIMA makes the variance constant and does not sufficiently capture volatility. Conversely, GARCH models do not only explicitly estimate time-varying conditional variance, but they are also appropriate to analyzing price uncertainty and shock persistence (IMF, 2023). However, GARCH models do not work well where there is a structural break or nonlinearity. Recent research indicates that machine learning methods like LSTM and Random Forest have been better at making short-horizon predictions compared to the traditional econometric models because they can learn nonlinear trends (World Bank, 2024). However, these models are not always interpretable as opposed to econometric models.

5.2 Cross-Country Evidence

The comparative analyses show that there is a relatively lower volatility in developed markets because they have more advanced infrastructure; they have more advanced risk management instruments and they have efficient information systems (OECD-FAO, 2024). However, in the case of developing economies, the volatility is increased by the causes of climatic vulnerability, under-developed storage facilities, and policy unpredictability (UNCTAD, 2023). Greater interconnection of the domestic markets to the commodity exchange markets around the world improves the efficiency of price transmission, yet it subjects the local markets to foreign shocks (World Bank, 2022).

This financial statement shows the extent to which a company is unstable or volatile in the short run or in the long run.
The short term volatility is also usually cyclical, based on seasonal production and temporary demand shocks. Climate change, demographic changes, and macroeconomic instability are the causes of long-term or structural volatility (IPCC, 2022). In comparison to cyclical volatility, structural volatility is likely to leave permanent welfare impacts.

5.4 Policy Effectiveness

Buffer stocks, export restrictions and support pricing have been variable towards price stabilization. Buffer stocks might lead to mitigation of short term spikes however, trade restrictions could enhance global price risks (IMF, 2024). Market effectiveness and food security goals will mean an effective policy (OECD-FAO, 2024).

6. Research Gaps and Challenges

Despite extensive empirical research on agricultural commodity price volatility, several critical gaps remain.
First, climate-risk models are not combined with mainstream price forecasting models in sufficient manners. Although climate change is considered a structural factor in the cause of agricultural instability in the long-term, the majority of econometric models do not dynamically reflect climate projections, extreme weather events, and yield-risk modeling (IPCC, 2022; FAO, 2023).
Second, insufficient details of a high-frequency analysis hamper the intra-day and short-cycle volatility trends. The bulk of the literature is based on monthly or yearly data, which can fail to capture short-term global market transmission between the more local market and global market (World Bank, 2024). Commodity market financialisation needs even more granular data to help reflect fast price spillage (IMF, 2023).
Third, there is still inadequate interdisciplinary integration. The studies of agricultural economics can often work independently of climate science, behavioral finance, and data science, which restricts the use of comprehensive models (OECD-FAO, 2024). Integrating weather prediction, macroeconomics, and artificial intelligence analytics may be extremely beneficial in relation to predictive power.
Fourth, in the volatility studies, smallholder vulnerability is not adequately represented. Though possessing a higher amount of income in price crashes, research on micro-level panel is scarce, especially in low-income States (UNCTAD, 2023).
Secondly, there are methodological problems that are related to data reliability, which may include missing market records, informal trading, and late reports of the data in developing economies (World Bank, 2022).
Lastly, predictive systems based on satellite data and digital marketplaces, which are fully realized in real-time and powered by IoT-ready supply chains, remain a nascent field, which is still missing the gap between study models and early-warning systems (FAO, 2023).

7. Future Research Directions

Future research on agricultural commodity price fluctuations should prioritize methodological innovation and interdisciplinary integration.
To begin with, prediction accuracy and interpretability can be improved with the help of combining artificial intelligence with the conventional econometric models. ARIMA-GARCH models together with a machine learning model, e.g., LSTM or Random Forest models have been shown to outperform ARIMA-

GARCHs in the short term forecasting performance in a volatile commodity market (World Bank, 2024; IMF, 2023). This kind of integration is able to get the linear dependencies and nonlinear volatility clustering.

Secondly, climate adaptive forecast models will be needed as extreme weather incidents increase. Projections of climate scenarios, and drought indices can be used to enhance the risk assessment in the long run in price modeling in applications (IPCC, 2022; FAO, 2023). Price forecasting systems should have dynamic climate-linked yield simulations embedded into them.

Third, big data analytics with the help of satellite imagery and remote sensing, as well as farm sensors based on the Internet of Things, provides real-time data on crop health and supply status. Such technologies allow identifying the shocks in production earlier and improve predictive abilities (OECD-FAO, 2024). Interest rate spatial data can also reinforce market integration analysis.

Fourth, blockchain technology opens the prospects of enhancing the supply chain transparency and reducing the information asymmetry. Seeing the books of transactions can minimize the distortions of speculative action and enhance the process of the price discovery (UNCTAD, 2023).

Fifth, ex-ante and ex-post effects of such interventions as buffer stocks, export restrictions, and minimum support pricing require a dynamic policy simulation model (World Bank, 2022).

Last but not least, a deep learning model based on commodity-specific characteristics, storage information, and trade patterns has the potential to be more accurate than a generalized forecasting system (FAO, 2023).

8. Conclusion

The discussion shows that commodity price fluctuations in agricultural markets are multi-dimensional by nature influenced by structural market conditions, macroeconomic channels of transmission, climatic uncertainties and market behavior in financialized markets. Recent events in the world have strengthened the interdependence of local agricultural markets and international economic systems on each other within the context of accidental shocks in supply chains induced by the pandemic, as well as unease due to geopolitical issues (World Bank, 2024; IMF, 2023). Production risks are further increased due to the same factors as climatic variability and long-term climate change, which are further causes of structural volatility (IPCC, 2022; FAO, 2023).

The conventional econometric methods like ARIMA and GARCH are still useful in determining the components of trend and modelling volatility clustering. Their predictive power can however be limited where there are nonlinear interactions as well as structural breaks. The new evidence indicates that machine learning models - especially LSTM and ensemble models - are better at short-term predictions by not only considering subtle trends within massive data, but also effectively predicting the future (OECD-FAO, 2024). Although this is so, interpretability and policy relevance are stronger in structural econometric models.

Thus, there is a need to integrate the approach of structural economic modeling with AI-based prediction systems. These hybrid systems have an ability to promote early-warning systems, market transparency, and evidence-based policymaking. Pricing stabilization policies have to balance between market efficiency and food security goals especially in the underdeveloped economies that are susceptible to external shocks (UNCTAD, 2023).

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