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Investigating Price Transmission and Lead-Lag Relationship of Selected Agri Commodities

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Abstract

The concept of the lead-lag relationship in finance is instrumental in enhancing the understanding of price discovery and risk management, as it elucidates how different assets interact and influence each other's price movements. This lead-lag relationship is used to understand market patterns, investor behavior, potential opportunities, and insightful information. This paper investigates the dynamics of the lead-lag relationship in financial market and its implications for investment decision-making. The study analyzes spot and futures prices (near, next, and far-month contracts) for agricultural commodities, including guar gum, guar seed, castor, cotton, cotton oilseed, and dhaniya, sourced from the National Commodities and Derivatives Exchange (NCDEX) spanning from April 2015 to September 2024 by employing Augmented Dickey-Fuller (ADF) test and granger causality test. The study revealed that guar gum, guar seed, castor, cotton, cotton oil seed and dhaniya commodity spot prices do not influence the future prices. There was no causal relationship between the selected agricultural commodities spot prices and future prices. This may be attributed to factors such as fluctuations in supply and demand, market news, seasonality, interest rates, and geopolitical developments. Finally, it helps policymakers to forecast economic conditions more accurately and design anticipatory measures. Central banks can use lead-lag analysis to anticipate inflation or economic downturns. If certain economic indicators (like consumer demand or industrial output) tend to inflation, the central bank can adjust interest rates proactively.

Keywords: Agricultural Commodities, Granger Causality Test, Lead-Lag Relationship, Spot and Future Prices.

Introduction

In the Indian economy, agricultural commodities play an indispensable role, serving as decisive inputs for food production and contributing significantly to trade and economic development. It produces a wide range of commodities, such as wheat, turmeric, soybean, cotton, castor, oilseeds, grains, fruits, vegetables and livestock. The agricultural sector in India is expected to grow to a value of US $24 billion by 2025, according to Inc42. Retail accounts for 70% of sales in the sixth-largest food and grocery market in the world, which is India. A sum of Rs. 1.52 lakh crore (US $18.26 billion) has been allocated for agriculture and related sectors in the Union Budget 2024–2025. The five most traded commodities on NCDEX are Guar Seed, Guar Gum, Jeera, Cotton Cake, and Turmeric. The mean daily turnover during 2023-2024 was ₹848 crores. The highest turnover attained in a single day during 2023-24 was noted at 2027 Crores. In the fiscal year 2023-24, the yearly turnover for guar gum on the National Commodity and Derivatives Exchange (NCDEX) in India amounted to ₹4,489.40 Crores. The yearly traded volume of castor seeds from April 2023 to March 2024 was 14,339.86. The aforementioned figures highlighted the importance of commodities trade in India. Producers, traders, and policymakers must comprehend the pricing processes of commodities exchanged in marketplaces such as the Multi Commodity Exchange (MCX) and the National Commodity & Derivatives Exchange (NCDEX) in India. Two fundamental concepts spot prices and futures prices are essential to this comprehension. Spot prices refer to the current market price at which a specific agricultural commodity can be bought or sold for immediate delivery. In contrast, future prices represent the agreed-upon price for delivering a commodity at a specified future date. These prices are determined in future markets, which allow participants to hedge against future price fluctuations and mitigate the risks associated with volatility in spot prices. Futures prices generally show expected supply and demand,

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acting as future indicators, while spot prices offer a current view. Futures markets help agriculture by discovering prices, transferring risk, and enhancing efficiency. Participants like farmers and investors use futures to secure prices and manage risk, affecting both individual market players and global economic conditions. Several key factors characterize the relationship between spot and futures prices. The basis is defined as the difference between the spot price and the futures price, which can fluctuate based on the costs of storage, transportation, and various market conditions. In the global stock market, a lead-lag relationship means that while one financial asset or market indicator moves, it precedes or lags behind the movement of another. It could aid potential investors in making appropriate investment decisions. This kind of relationship between stocks, indices, sectors and commodities can be observed in financial markets. The lead-lag relationship can assist potential investors by offering valuable and dynamic insights about financial market trends and opportunities. Investors can adjust their investment strategies based on the lead or lag behavior of financial instruments traded in the stock market. Even though lead-lag relationships provide valuable insights into the market, it is essential to understand that information may not always be useful in generating profits because of market uncertainties. Different factors, such as demand and supply, seasonality, Interest rates, and geographical factors, can influence stock price movements. However, sophisticated algorithms and trading strategies are available to understand lead-lag relationships and generate profits. Investors can use multiple techniques to identify the lead-lag relationship in financial markets. Some techniques are Scatter plots, lagged scatter plots, and the Granger causality test. One of the common techniques used to test the lead-lag relationship is the Granger causality test, which describes which assets are leading or lagging behind others. Investors, academicians, and familiar people assume that Future contract prices will influence spot prices and vice versa. However, this study concluded that such assumptions were wrong, did not exist, and exposed any relationship among them. Agricultural commodities' spot and future prices exhibited diverse price movements due to differences in factors such as production cycles, seasonal patterns, and global trade dynamics. This heterogeneity can make it challenging to identify a consistent lead-lag relationship with spot and future contracts. Exogenous shocks in carbon emission trade and stock markets in China were examined using the non-parametric thermal optimal route methodology.' The study revealed that the stock market frequently leads the carbon market on the majority of trade days; however, when external variables substantially influence the average returns of the carbon market, this connection may invert. The research indicates a complicated interaction between various markets that requires more examination, especially during times of economic instability. When markets decline below zero, the carbon market subsequently influences the stock market. The study revealed significant diverse effects of several external shocks on the lead-lag relationship between the two markets, encompassing government policy, the Sino-U.S. trade conflict, and the COVID-19 pandemic. The aforementioned results enhance comprehension of financial markets in China, allowing investors to incorporate carbon stocks into their portfolios for profit generation (1). The detection of lead-lag relationships using lagged multi-factor models was studied through dynamic time warping. This work developed a cluster-driven technique for the robust identification of lead-lag interactions using dynamic temporal warping and lagged multi-factor models. Their work has shown that in multivariate time series systems, there are lead-lag connections that indicate interdependence between time series when temporally offset from one another. Understanding the temporal interdependence among various time series enhances comprehension of the intricate interactions and patterns within the system. Ultimately, they determined that their algorithm could effectively identify lead-lag links in financial markets, facilitating the development of trading strategies (2). The relationship between the prices of steel materials and related products over different periods was studied using network analysis. This research examined two significant steel materials in midstream and downstream steel products over several times to analyse their pricing interdependencies. The researchers used a method called the maximum overlap discrete wavelet transform (MODWT), along with cross-correlation and the Podobnik test, to break down the original steel materials and to calculate and evaluate how the prices of the two steel materials relate to the prices of 16 steel products over time. Ultimately, they established 12 price lead-lag relationship networks to analyse the price impact of the two materials over various temporal scales. The analysis revealed that the prices of scrap steel products exhibited fluctuations at the same time lag order, although iron ore mostly influenced most steel product prices. The goods in the downstream industrial chain often depended on iron ore. Ultimately, the correlations between steel materials and steel products intensify as the temporal scale extends (3). The lead-lag relationship between China's crude oil futures and spot markets was examined. It used the one-minute high-frequency prices by applying the thermal optimal path (TOP) method and the Mixed Frequency Data Sampling Regression (MIDAS) model to assess the predictive capacity of high-frequency prices in the futures market relative to the spot market from March 2018 to December 2021. The statistical findings indicated that, mostly, futures markets precede the spot market. Additionally, it was shown that 60-minute high-frequency futures prices are the most indicative of daily spot data, whereas the predictive capacity of crude oil futures diminished during the COVID-19 outbreak and exhibited greater productiveness during periods of night trading. This research has significant consequences, serving to advise investors and provide empirical data and credible information for policymakers (4). The Joint Dynamic Topic Model was used to explore a lead-lag connection in two text corpora.' Their research formulated an embedding extension model using the joint dynamic topic model to tackle the modeling challenge for temporal data. By integrating various dimensions of text analysis, they aimed to enhance the understanding of how topics evolve over time and influence one another within the crop a large-scale text corpus. Ultimately, they evaluated the two text corpora, including statistical articles and graduation theses, using the suggested approach. The results showed that the suggested model successfully found the lead-lag relationship between the two text groups and highlighted specific and shared topics for future research (5). Conventional time series methodologies were used to examine industrial output and foreign commerce in Malaysia.' The research observed a unidirectional link between the two nations, flowing from commerce to industrial output. Trade openness often augments industrial productivity via technical transfer. This study's principal empirical result about Malaysia is that international commerce is driving industrial development, similar to several other open economies in East Asia. The findings were logical and credible, including significant policy implications for Malaysian economic strategies. By fostering trade relationships and enhancing foreign investment, policymakers can further stimulate industrial growth and maintain competitiveness in the global market (6). The three indices: Bank Nifty, CNX IT, and Mini Nifty were used to examine Indian financial markets. This study examines the lead-lag relationship between spot and futures prices from their inception to February 9, 2012. The objective of the study is to determine the relationship between the futures market and the spot market, specifically whether the former leads or lags in comparison to the latter. The research gathered data from the NSE website and utilised the Granger causality and Johansen cointegration tests to analyse the relationship among the three chosen indices. The test statistics indicated that futures markets precede spot markets in the chosen indices (7). The daily dynamic trends of the stock market were examined. The daily lead-lag relationship between stock pairs was tested using a variety of statistical methodologies. However, they discovered that the exponential random graph model and the power-law distribution were more suited for the investigation. Ultimately, they worked to identify new methods for defining the lead-lag effect in the financial sector (8). The exploration was conducted on diverse financial markets, including Brent oil, global stocks, green investments, cryptocurrency, and Islamic markets. The research concentrated on analysing tail reliance and lead-lag interactions in both bullish and bearish settings. The research investigated the lead-lag connection via copula and wavelet methodologies, analyzing data from January 2014 to December 2022. The findings revealed unique patterns of interdependence and interaction across the analyzed financial markets. Nonetheless, a significant exception occurred in the Brent and cryptocurrency markets, where the correlation may extend to the green market throughout both bullish and negative phases. Subsequent analysis revealed that the highest correlation peaked at 38% between Brent and green markets during bullish phases, in contrast to only a 7% correlation during negative phases. A 25% correlation exists between global and green markets and a 5% correlation between Brent and cryptocurrency markets throughout both bullish and negative phases (9). The lead-lag impact in the stock market was investigated. This study examined the lead-lag impact on individual stocks relative to the CSI 300 index in the Chinese stock market using a stochastic actor-orientated model. Preliminary research examined the correlation between the lead-lag network and the features of equities using a complex network lens. Key elements such as market capitalisation, trade volume, and financial performance establish lead-lag correlations (10).

The relationship between credit default swap premiums (CDS) and government bond yield spreads (GBS) during a major financial crisis in Italy was studied. The study examined the lead-lag connection using co-integration, the vector error correction model, and the Granger causality test. The research indicated that Italy experienced financial strain throughout the study period, which was attributed to sluggish GDP growth and elevated public debt. This resulted in market volatility (11). The SSESTM model was used to investigate the US and Japanese stock markets. The SSESTM (Supervised Sentiment Extraction via Screening and Topic Modelling) approach was used to assess the lead-lag impact and sentiments, as well as to forecast future stock returns. The United States and Japanese stock markets significantly benefitted from the use of the SSESTM model. The researcher found that their proposed technique provided evidence for generating and predicting future stock returns by analysing attitudes among causally related firms (12). Price discovery in the Turkish Stock Exchange and futures markets using the ISE 100 indexes was examined.' The study examined 100 stock index futures markets in Turkey from 2006 to 2011. They examined the lead-lag impact and long-term link between futures and spot markets using co-integration and vector error correction models. The findings indicated that the futures market in Turkey served as an effective price discovery mechanism, with current futures prices in one market influencing changes in current spot prices. Finally their findings revealed a significant relationship between spot prices and futures prices, indicating that information flows between these markets can enhance price efficiency and reduce arbitrage opportunities (13). The Granger causality test and daily data from Turkey spanning from February 2005 to March 2011 were used to investigate the Istanbul Stock Exchange (ISE) 30 spot and futures markets. Their findings suggested that future pricing would influence spot prices consequently; they determined that investors might allocate their capital to the Turkish stock market based on future contract values (14). The spot and futures contracts of Greece (FTSE/ASE-20 and FTSE/ASE Mid 40) from the Athens Derivatives Exchange (ADEX) during the crisis from 1999 to 2001 were investigated using the Bivariate GARCH model to explain how prices are set in both markets. Evidence indicates that the futures market helps set prices and contains important information about spot prices, consistent with other similar studies. Evidence indicates that the futures market helps determine prices, meaning that future prices contain important information about spot prices, which agrees with similar studies. This finding underscores the significant role of futures markets in enhancing the efficiency of price formation in volatile periods. Moreover, it suggests that market participants should consider futures prices as a vital indicator when making investment decisions in the underlying spot markets. These results are beneficial to financial managers and traders engaged with Greek stock index futures (15).

A mathematical framework was used to investigate intermarket interactions in financial markets. The research looked at how prices change in two connected markets by measuring the differences in key points on their charts, which showed how the price trends shifted, leading to a circular pattern. They found that several financial instruments in foreign currency, commodities, and indices exhibited substantial correlations. On several occasions, one of the two markets significantly advanced in relation to the relevant local extrema, suggesting a non-zero phase shift between them (16). The lead-lag relationship between spot and futures has been investigated using agricultural commodities from various countries. They employed methodologies, such as cointegration and Granger causality tests, to analyse the data. Their findings indicated that futures prices often lead spot prices, suggesting that traders could benefit from using futures as a predictive tool for market movements. They used factors such as long-term equilibrium, the power of short-term correlation, Granger causality, information sharing, and spillover impact to quantify the lead-lag relationship. They discovered that seasonality and asymmetric market volatility significantly influenced the dynamics of these relationships. Their findings suggest that understanding these factors can enhance forecasting models and improve decision-making for investors in the agricultural market. They were the root causes of price hazards. They also discovered that traders, regulators, and bullish news all had an impact on commodity stock prices (17). The spot and future prices of the Indian stock market from 2009 to 2020 have been examined. They selected aluminium, copper, crude oil, nickel, and silver for the empirical process, and they considered agriculture, livestock, and precious metals. They employed the ARDL model, VECM model, and Granger causality techniques for data analysis. Finally, the study concluded unidirectional causality existed between spot and future markets (18). The randomness and efficiency dynamics of Indian exchanges were investigated. The efficient market hypothesis (EMH) and the adaptive market hypothesis (AMH) were used to study the behaviour of randomness and efficiency in the Indian market. The study found no uniformity or random patterns, and its performance varies over time. While inefficient ties were evident during the study period (1990-2014), performance improvements were observed in some periods, signifying greater adaptability in the BSE Sensex and NSE Nifty markets (19).

A study on IPO returns on national exchanges has been conducted. Their research examined 463 IPOs listed on the National Stock Exchange (NSE) between January 2000 and August 2018. They found that the average listing yield was 20.10%, which is significantly higher than the average market yield of 0.24%. Out of the 463 IPOs, 66.74% achieved positive share price returns, indicating that these IPOs were undervalued. However, it is important to note that not all IPOs are undervalued; 33.26% of IPOs were overvalued, leading to negative stock returns. According to this study, a retail investor could have earned 99% more returns by investing in all IPOs (over an 18-year period) and selling them on the trading day (20).

The literature review concludes that while several studies explored lead-lag relationships in financial markets (stocks, oil, credit, etc.), there is a relative scarcity of research specifically focusing on agricultural commodity futures and spot markets. Existing studies often treat commodities as a homogenous group. However, agricultural commodities are diverse; each with it owns supply chain, storage characteristics, and market participants. Therefore, this study focuses on specific agricultural commodities.

Methodology

The dataset consists of daily trading prices of guar gum, guar seed, castor, cotton, cotton oil seed, dhaniya, spot, near, next, and far month contract prices spanning from April 2015 to September 2024 from the National Commodity and Derivatives Exchange of India Ltd (NCDEX). The current study employs experimental research and a quantitative research design. It used statistical methods such as the augmented Dickey-Fuller test to check the stationarity of the data, lag length criteria to determine the best number of past values to include, and the Granger causality test to see how the variables influenced each other over time. Study developed the following steps for data analysis.

Step: 1 Unit root test using ADF test

Step.2 checking Lag length criteria

Step.3 Pairwise Granger causality test

This study formulated six null hypotheses to test lead-lag association among the selected Agricultural commodities. They are

H0: There is no lead-lag relationship between guar gum spot prices and near, following, and far-month contract prices.

H1: There is a lead-lag relationship between guar gum spot prices and near, following, and far-month contract prices.

H0: No lead-lag relationship between Guar seed spot prices and near, next, and far-month contract prices.

H1: There is a lead-lag relationship between guar seed spot prices and near, next, and far-month contract prices.

H0: No lead-lag relationship between Castor Spot Prices and Near, Next and Far month contract prices.
H1: There is a lead-lag relationship between Castor Spot Prices and near, next, and far-month contract prices.
H0: No lead-lag relationship exists between cotton spot prices and near, next, and far-month prices.
H1: A lead-lag relationship exists between cotton spot prices and the prices of the near, next, and far months.
H0: No lead-lag relationship exists between cotton seed oil spot prices and near, next, and far-month contract prices.
H1: A lead-lag relationship exists between the spot prices of cotton oil seed and the futures contract prices for the near, next and far months' prices
H0**:** There is no lead-lag relationship between Dhaniya spot prices and near, next, and far-month contract prices.
There is a lead-lag relationship between Dhaniya spot prices and near, next, and far-month contract prices.

Results and Discussion

Table 1 presents the ADF test results for guar gum, indicating the stationarity and non-stationarity of the variables. The test results indicated P values of 0.2719, 0.2131, 0.2814, and 0.3414, all exceeding 0.05 at level 0, suggesting that the data is non-stationary. Afterwards, we evaluated the data at level 1, which revealed p-values below 0.05, indicating its stationarity and suitability for further analysis.
Table 2 shows the lag length criteria for spot and future prices of guar gum. It is a general guideline for using various view models. The Akaike Information Criterion (AIC) and Schwarz Information Criterion (SIC) are the most often used techniques for choosing lag length criteria. When choosing the lag duration of the spot and future prices of guar gum, the current study considered AIC. The outcome indicates that the fourth lag is the ideal latency.

Table 1: Unit Root Test between Spot and Future Prices of Guar Gum

Level	**First Difference**					
Variables	t-statistics	Critical Value	P-value	t-statistics	Critical Value	P-value
Spot	-2.034977	-3.433403	0.2719	-43.87172	-3.433404	0.0001
Near	-2.182055	-3.433406	0.2131	-37.30568	-3.433406	0.0000
Next	-2.010481	-3.433406	0.2824	-37.80689	-3.433406	0.0000
Far	-3.433406	-3.433406	0.3414	-38.1921	-3.433406	0.0000

Note: Significance at the 0.05% level

Table 2: Length Lag Criteria of Spot and Future Prices of Guar Gum

LAG	**LogL**	**LR**	**FPE**	**AIC**	**SC**	
0	-44586.97	NA	6.98e+15	44.99493	45.00339	44.99804
1	-39705.19	9743.872	5.11e+13	40.07786	40.11174	40.09032
2	-39599.23	211.1625	4.63e+13	39.98005	40.03930	40.00182
3	-39558.83	80.38696	4.49e+13	39.94837	40.03301*	39.97946*
4	-39548.54	20.45346	4.48e+13	39.94706*	40.05709	39.98748

Table 3: Granger causality test between Guar Gum Spot and Future Prices

Null Hypothesis	**Obs**	**F-Statistic**	**Prob.**
Guangum Near Month Future Prices Does not granger cause Guargum Spot Prices	2009	0.35773	0.6993
Guargum Spot Prices Does not granger cause Guangum Near Month Future Prices		0.05765	0.9440
Guangum Next Month Future Prices Does not granger cause Guargum Spot Prices	2009	2.20183	0.1109
Guargum Spot Prices Does not granger cause Guangum Next Month Future Prices		0.50593	0.6030

GuangumFar Month Future Prices Does not granger cause Guargum Spot Prices	2009	0.31900	0.7269
Guargum Spot Prices Does not granger cause Guangum Far Month Future Prices		0.60470	0.5463

Table 4: Unit Root Test between Spot and Future Prices of Guar Seed

	Level			First Difference		
Variables	t-statistics	Critical Value	P-value	t-statistics	Critical Value	Pvalue
Spot	-2.227334	-3.432783	0.1967	-48.60184	-3.432784	0.0001
Near	-2.517099	-3.432787	0.1114	-36.12844	-3.432787	0.0000
Next	-2.4499	-3.432787	0.1287	-36.56207	-3.432753	0.0000
Far	-2.308292	-3.43287	0.1694	-36.73453	-3.34327	0.0000

Note: Significance at the 0.05% level

Table 3 interprets the directional relationship between the guar gum spot, near-next, and far-month daily trading prices. Here, the probability values were more than 0.05, which indicates that there is no causal relationship between guar gum spot prices and guar gum near, next, and far month trading prices. Hence, it was inferred that there was no lead-lag association between guar gum spot and future markets. Table 4 presents the ADF test results for guar seed, indicating the stationarity and non-stationarity of the variables. The test results indicated P values of 0.1967, 0.1114, 0.1287, and 0.1694, all exceeding 0.05 at level 0, suggesting that the data is non-stationary. Afterwards, we evaluated the data at level 1, which revealed p-values below 0.05, indicating its stationarity and suitability for further analysis. Table 5 shows the lag length criteria for spot and future prices of guar seed. It is a general guideline for using various view models. The Akaike Information Criterion (AIC) and Schwarz Information Criterion (SIC) are the most often used techniques for choosing lag length criteria. When choosing the lag duration of the spot and future prices of guar seed, the current study considered AIC. The outcome indicates that the fourth lag is the ideal latency. Table 6 elucidates the directional correlation among the daily trading prices of Guar Seed Spot, Near, Next, and Far Month. The probability value was below 0.05, indicating that guar seed near-month contract prices influence the spot prices. Probability values exceeded 0.05 for both next and far month contracts, indicating that the prices of these contracts do not influence the spot prices of guar seed, and vice versa. Consequently, we deduced that no lead-lag relationship existed between the spot prices of Guar seed and the futures markets, with the exception of near-month contract prices.

Table 5: Lag length Criteria of Spot and Future Prices of Guar Seed

Lag	Logl	LR	FPE	AIC	SC	HQ
0	-54384.66	NA	7.82e+18	54.85492	54.86620	54.85907
1	-47128.95	14474.82	5.27e+15	47.41017	47.60955	47.57387
2	-46971.19	314.0960	4.57e+15	47.41017	47.51170*	47.44747
3	-76913.32	114.9778	4.38e+15	47.36794	47.51459	47.42181*
4	-46890.19	45.85762	4.35e+15	47.36076*	47.55253	47.43120

Table 6: Granger Causality Test between Guarseed Spot and Future Prices

Null Hypothesis	Obs	F-Statistic	Prob.
Guarseed Near Month Future Prices Does not granger cause Guarseed Spot Prices	2086	3.31236	0.036
Guarseed Spot Prices Does not granger cause Guar seed Near Month Future Prices		0.48455	0.616
Guarseed Next Month Future Prices Does not granger cause Guarseed Spot Prices	2085	0.08690	0.916
Guarseed Spot Prices Does not granger cause Guarseed Next Month Future Prices		0.14182	0,086

Guarseed Far Month Future Prices Does not granger cause Guarseed Spot Prices	2084	0.39509	0.673
Guarseed Spot Prices Does not granger cause Guarseed Far Month Future Prices		0.05004	0.951

Table 7: Unit Root Test between Spot and Future Prices of Castor

	Level			First Difference		
Variables	t-statistics	Critical Value	P-value	t-statistics	Critical Value	P-value
Spot	-1.671649	-3.433559	0.4456	-30.1169	-3.433559	0.0000
Near	-1.396594	-3.433557	0.5885	-48.0094	-3.433558	0.0001
Next	-1.690573	-3.433557	0.4359	-49.3888	-3.433557	0.0001
Far	-1.665477	-3.433557	0.4488	-47.0112	-3.433557	0.0001

Note: Significance at the 0.05% level

Table 8: Lag Length Criteria of Spot and Future Prices of Castor

Lag	Logl	LR	FPE	AIC	SC	HQ
0	-52945.70	NA	2.46e+19	56.00180	56.01353	56.00612
1	-43048.75	19741.57	7.12e+14	45.55129	45.60994	45.57289
2	-42977.57	141.6760	6.72e+14	45.49294	45.59850*	45.53181*
3	-42964.52	25.92071	6.74e+14	45.49606	45.64853	45.55220
4	-42946.16	36.39657	6.73e+14	45.49356*	45.69295	45.56698

Table 9: Granger Causality Test between CastorSpot and Future Prices

Null Hypothesis	Obs	F-Statistic	Prob.
Castor Near Month Future Prices Does not granger cause Castor Spot Prices	1916	4.07101	0.017
Castor Spot Prices Does not granger cause Castor Near Month Future Prices		4.0794	0.016
Castor Next Month Future Prices Does not granger cause Castor Spot Prices	1915	1.60066	0.202
Castor Spot Prices Does not granger cause Castor Next Month Future Prices		0.58154	0.559
Castor Far Month Future Prices Does not granger cause Castor Spot Prices	1914	0.80219	0.448
Castor Spot Prices Does not granger cause Castor Far Month Future Prices		2.89745	0.55

Table 7 presents the ADF test results for castor, indicating the stationarity and non-stationarity of the variables. The test results indicated P values of 0.4456, 0.5885, 0.4359, and 0.4488, all exceeding 0.05 at level 0, suggesting that the data is non-stationary. Afterwards, we evaluated the data at level 1, which revealed p-values below 0.05, indicating its stationarity and suitability for further analysis. Table 8 shows the lag length criteria for spot and future prices of castor. It is a general guideline for using various view models. The Akaike Information Criterion (AIC) and Schwarz Information Criterion (SIC) are the most often used techniques for choosing lag length criteria. When choosing the lag duration of the spot and future prices of castor, the current study considered AIC. The outcome indicates that the fourth lag is the ideal latency. Table 9 elucidates the directional correlation among the daily trading prices of Castor Spot, Near Next, and Far Month. The probability values for Castor Near Month contracts were below 0.05, indicating that Castor spot prices influence Castor Near Month contract prices and vice versa. Consequently, it was deduced that a lead-lag relationship existed between Castor Spot and future markets about near-month contracts and spot prices. For Castor Next and far-month contracts, P values exceeded 0.05, indicating that Castor Spot Prices lack any lead-lag relationship with Next and far-month contract prices. Table 10 presents the ADF test results for cotton, indicating the stationarity and non-stationarity of the variables. The test results indicated P values of 0.2686, 0.4992, 0.6160, and 0.6284, all exceeding 0.05 at level 0, suggesting that the data is non-stationary. Afterwards, we evaluated the data at level 1, which revealed p-values below 0.05, indicating its stationarity and suitability for further analysis.

Table 10: Unit Root Test between Spot and Future Prices of Cotton

	Level			**First Difference**		
Variables	t-statistics	Critical Value	P-value	t-statistics	Critical Value	P-value
Spot	-2.042623	-3.432410	0.2686	-10.97998	-3.432410	0.0000
Near	-1.567482	-3.432397	0.4992	-37.82133	-3.432397	0.0000
Next	-1.333575	-3.432397	0.6160	-27.03890	-3.432397	0.0000
Far	-1.307149	-3.432400	0.6284	-24.91157	-3.432400	0.0000

Note: Significance at the 0.05% level

Table 11: Lag Length Criteria of Spot and Future Prices of Cotton

Lag	**Logl**	**LR**	**FPE**	**AIC**	**SC**	**HQ**
0	-84403.06	NR	1.85e+26	71.83579	71.83560	71.83936
1	-75365.85	18035.96	8.85e+22	64.15817	64.20721	64.17603
2	-69629.07	11429.61	6.59e+20	59.28942	59.37769	59.32157
3	-68653.01	1941.316	2.91e+20	58.47235	58.59986	58.51879
4	-68385.90	530.3609	2.35e+20	58.25864*	58.42538	58.31936

Table 11 indicates the Lag length criteria of Spot & Future Prices of Cotton. The Akaike Information Criteria (AIC) and Schwarz Information Criteria (SIC) are the most often used techniques for choosing lag length criteria. When choosing the lag duration of the spot and future prices of cotton, the current study considered AIC. The outcome indicates that 4thlag is the ideal latency. Table 12 analyses the directional relationship among the monthly trading prices of cotton spot, near, next, and far monthly contracts. The probability values exceeded 0.05, suggesting that cotton spot prices do not influence Cotton Near, Next, and Far Month prices, and vice versa. It was concluded that no lead-lag relationship exists between Cotton Spot and future Markets. Table 13 presents the ADF test results for cotton oil seed, indicating the stationarity and non-stationarity of the variables. The test results indicated P values of 0.0662, 0.001, 0.2128, and 0.1194, all exceeding 0.05 at level 0, except in the case of near month contratprics, suggesting that the data is non-stationary. Afterwards, we evaluated the data at level 1, which revealed p-values below 0.05, indicating its stationarity and suitability for further analysis.

Table 12: Granger Causality Test between Cotton Spot and Future Prices

Null Hypothesis	**Obs**	**F-Statistic**	**Prob.**
Cotton Near Month Future Prices Does not granger cause Cotton Spot Prices	2023	0.05704	0.944
Cotton Spot Prices Does not granger cause Cotton Near Month Future Prices		0.0916	0.981
Cotton Next Month Future Prices Does not granger cause Cotton Spot Prices	2022	0.09599	0.908
Cotton Spot Prices Does not granger cause Cotton Next Month Future Prices		0.03853	0.962
Cotton Far Month Future Prices Does not granger cause Cotton Spot Prices	2022	0.09599	0.908
Cotton Spot Prices Does not granger cause Cotton Far Month Future Prices		0.03853	0.962

Table 13: Unit Root Test of Spot and Future Prices of Cotton Oil Seed

	Level			**First Difference**		
Variables	t-statistics	Critical Value	P-value	t-statistics	Critical Value	P-value
Spot	-2.769642	-3.432936	0.0662	-46.04149	-3.432937	0.0001
Near	-4.74910	-3.432949	0.0001	-22.33088	-3.432952	0.0000
Next	-2.182917	-3.432966	0.2128	-9.965446	-3.4329966	0.0000
Far	-2.182917	-3.432955	0.1194	-12.35505	-3.432960	0.0000

Note: Significance at the 0.05% level

Table 14: Lag Length Criteria of Spot and Future Prices of Cotton Oil Seed

Lag	**LogL**	**LR**	**FPE**	**AIC**	**SC**	**HQ**
0	-69471.93	NA	6.53e+20	59.27980	59.28963	59.28338
1	-60230.22	18444.00	2.49e+17	51.40804	51.45718	51.42593
2	-59811.29	834.6408	1.77e+17	51.06424	51.15270*	51.09646
3	-59750.62	120.6543	1.70e+17	51.02613	51.15390	51.07267
4	-59704.93	90.72952	1.66e+17	51.00079*	51.16788	51.06165

Table 15: Granger Causality Test between Cotton Oil Seed Spot and Future Prices

Null Hypothesis	**Obs**	**F-Statistic**	**Prob.**
Cotton Oil Seed Near Month Future Prices Does not granger cause Cotton Oil Seed Spot Prices	2047	0.07692	0.926
Cotton Oil SeedSpot Prices Does not granger cause Cotton Oil Seed Near Month Future Prices		3.74990	0.023
Cotton Oil Seed Next Month Future Prices Does not granger cause Cotton Oil Seed Spot Prices	2046	14.6885	5E-0
Cotton Oil Seed Spot Prices Does not granger cause Cotton Oil Seed Next Month Future Prices		3.50383	0.030
Cotton Oil Seed Far Month Future Prices Does not granger cause Cotton Oil Seed Spot Prices	2045	1.72578	0.178
Castor Oil Seed Spot Prices Does not granger cause Cotton Oil Seed FarMonth Future Prices		3.48490	0.087

The Table 14 presents the Lag length criteria of Spot & Future Prices of Cotton oil seed. The Akaike Information Criteria (AIC) and Schwarz Information Criteria (SIC) are the most often used techniques for choosing lag length criteria. When choosing the lag duration of the spot and future prices of cotton oil seed, the current study considered AIC. The outcome indicates that 4thlag is the ideal latency. Table 15 elucidates the directional correlation among the daily trading prices of cotton oil seed Spot, Near, Next, and Far Month. The likelihood value was below 0.05 for the year and next-month contracts, suggesting that the prices of Cotton Oil Seed Near and next-month futures influenced spot prices. Consequently, we deduced the existence of a lead-lag relationship between Cotton Spot and future markets with regard to near-next-month contracts and spot prices. The P-value for the Cotton Oil Seed Far Month Contract exceeded 0.05, indicating no lead-lag relationship between Cotton Oil Seed Spot pricing and Month Contract pricing. Table 16 presents the ADF test results for Dhaniya, indicating the stationary and non-stationarity of the variables. The test results indicated P values of 0.1755, 0.1078, 0.1932, and 0.1198, all exceeding 0.05 at level 0, suggesting that the data is non-stationary. Afterwards, we evaluated the data at level 1, which revealed p-values below 0.05, indicating its stationarity and suitability for further analysis.

Table 17 present about the Lag length criteria of Spot & Future Prices of Dhaniya.The Akaike Information Criteria (AIC) and Schwarz Information Criteria (SIC) are the most often used techniques for choosing lag length criteria. When choosing the lag duration of the spot and future prices of dhaniya, the current study considered AIC. The outcome indicates that 4th lag is the ideal latency.

Table 16: Unit Root Test between Spot and Future Price of Dhaniya

	Level			First Difference		
Variables	t-statistics	Critical Value	P-value	t-statistics	Critical Value	P-value
Spot	-2.289513	-3.432385	0.1755	-54.07717	-3.432386	0.0001
Near	-2.532768	-3.432388	0.1078	-36.15684	-3.432388	0.0000
Next	2.237031	-3.432391	0,1932	-27.00903	-3.432391	0.0000
Far	-2.482897	-3.432392	0.1198	-18.52557	-3.432392	0.0000

Note: Significance at the 0.05% level

Table 17: Lag Length Criteria of Spot and Future Prices of Dhaniya

Lag	Logl	LR	FPE	AIC	SC	HQ
0	-72452.28	NR	7.09e+21	61.66492	61.67473	61.66849
1	-61471.67	21914.51	6.28e+17	52.33333	52.38237	52.35119
2	-61398.23	146.3142	5.98e+17	52.28445	52.37272*	52.31660
3	-61345.96	103.9584	5.80e+17	52.25358	52.38109	52.30002*
4	-61317.32	56.87428	5.74e+17	52.24282*	52.40956	52.30354

Table 18: Granger Causality Test between Dhaniya Spot and Future Prices

Null Hypothesis	Obs	F-Statistic	Prob.
Dhaniya Near Month Future Prices Does not granger cause DhaniyaSpot Prices	2034	3.844815	0.021
Dhaniya Spot Prices Does not granger cause Dhanya Near Month Future Prices		1.42501	0.240
Dhaniya Next Month Future Prices Does not granger cause Dhaniya Spot Prices	2033	1.26546	0.282
Dhaniya Spot Prices Does not granger cause Dhaniya Next Month Future Prices		1.04313	0.352
Dhaniya Far Month Future Prices Does not granger cause Dhaniya Spot Prices	2032	1.71422	0.180
Dhaniya Spot Prices Does not granger cause Dhaniya Far Month Future Prices		0.38901	0.677

Table 18 elucidates the directional correlation among the daily trading prices of Dhaniya Spot, Near Month, Next Month, and Far Month. The P-value for near-month contract prices was below 0.05, indicating that these prices influence spot prices. In the instance of the Next and Far Month Contract, P values above 0.05 indicate that the prices of the Next and Far Month Contract did not influence spot prices, nor did spot prices affect them. Consequently, it was concluded that no lead-lag relationship exists between Dhaniya Spot and future markets, except in near-month contract prices.

Conclusion

The results of the study demonstrate that spot prices for guar gum have no effect on prices for guar gum in the near and next months and vice versa. The daily trade prices influence spot pricing for guar seeds for the next month, but not the other way around. Furthermore, the spot prices of guar seeds have no bearing on future month prices, and neither do future month contract prices. Spot prices for castor are higher than near-month pricing, although this is not the case in other months. There is no discernible trend in cotton prices between current and upcoming months. Cotton oil seed spot prices impact near-month prices but not far-month prices. In contrast, future contract prices have no affected on spot prices and Dhaniya's near-month contract prices affect spot prices. The study concludes that spot prices cannot forecast future prices and vice versa. This fluctuation is driven by factors such as shifts in supply and demand, market news, seasonal variations, interest rate fluctuations, and geopolitical events. As a result, investors are advised not to rely on the correlation between spot and futures markets when making investment decisions. In April 2015, the price of guar gum per quintal was Rs. 7,533, which increased to Rs. 11,864 by September 2024, signifying a supply deficiency relative to demand. As a result, prices fluctuated regularly. Significant occurrences in the agriculture sector from 2015 to 2024 include diminished productivity, economic recession, and governmental pledges. There has also been resistance from farmers and governmental interventions. Agricultural income has increased by 5.23% annually during the past decade. The Gross Value Added (GVA) of agricultural and related industries rose from 24.38% in FY15 to 30.23% by FY23. The area of land used by microirrigation systems increased to approximately 8,000 hectares between 2015 and 2023. Kisan Credit Cards As of March 2024, 77.5 million Kisan Credit Card accounts were active. The aforementioned facts served as evidence against the non-existence of a lead-lag relationship between spot and future pricing.

This study employed daily closing prices of guar gum, guar seed, Castor, cotton, cotton oil seed and dhaniya. However, intraday commodity data is more conclusive and accurate when describing commodity markets. This study is confined to the lead-lag relationship to discover a correlation between spot and future prices. It can be extended by considering other Agri commodities, non-agri commodities, and indexes with other risk aspects. In general, the investment community believes that future prices are based on spot prices. This study proved that the general note was incorrect and that there was no correlation between the selected commodities spot and future prices. This research helps the producers, farmers, and investment community to understand agricultural commodity spots and future market prices, which will help maximise their return in the near future. Finally, this study helps policymakers to forecast economic conditions more accurately and design anticipatory measures. Central banks can use lead-lag analysis to anticipate inflation or economic downturns. If certain economic indicators (like consumer demand or industrial output) tend to lead to inflation, the central bank can adjust interest rates proactively.

Abbreviations

None.

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Author Contributions

P. Lakshmi Narasa Reddy: Making concept, writing article, analysing the data, S. Visalakshmi: Evaluating and reviewing the article, conducting the validation and finalistion and submission.

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