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Empirical Investigation of Spot and Future Prices of Refined Soy Oil and RM Seed: Unveiling Price Discovery and Volatility Spillover Dynamics

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Abstract

Indian agricultural commodity market is subjected to price volatility due to several domestic and global variables causing price risk to farmers, traders, and consumers. This research paper investigates the price discovery and volatility spillover between spot and future prices of refined soy oil and RM seeds traded on the National Commodity and Derivative Exchange (NCDEX) over ten years from 2011 to 2021. The study has used advanced econometric models for estimating cointegration, Granger causality and volatility spillover among the two markets. The results of Johansen cointegration test indicate a long-run cointegration whereas pair wise Granger causality test reveals a bi-directional casual relationship between the spot and future prices of select commodities. The ARCH model has been employed to establish the presence of time varying conditional volatility and persistence of volatility shocks, confirming the presence of ARCH effect which is a precondition for using GARCH model. The estimates of diagonal BEKK-GARCH model reveal a significant volatility spillover effect between the spot and future prices of refined soy oil and RM seed. The findings highlight the need for transparency and efficiency in the Indian agricultural commodity market to protect the interests of producers, investors and other stakeholders.

Keywords: Commodity markets, price discovery, volatility spillover, global variables, Granger causality.

Introduction

India's vast geographical expanse and favorable climatic conditions have made it a leading producer and exporter of various agricultural commodities, including spices, cereals, vegetable oil, and oil seeds. However, the Indian agricultural commodity market, like other global markets is not immune to price fluctuations. Volatility in the agricultural commodities market refers to the rapid and unpredictable price fluctuations that can occur due to demand-supply dynamics as well as multiple other factors. These factors range from weather patterns and natural disasters to global demand and supply shifts, government policies, market speculation etc. The impact of volatility can be particularly significant in the case of vegetable oil markets and oil seeds markets, which play crucial roles in India's domestic consumption, and international trade and have a prominent effect on the livelihoods of millions of farmers. Agriculture production in India depends upon the vagaries of monsoon and creates uncertainties in crop prices. The price of agricultural commodities also depends upon numerous controllable and uncontrollable factors and shows high price volatility, resulting in financial risk to farmers, traders and manufacturers. The volatility in the commodity markets can have profound implications for the stakeholders involved in the supply chain. Therefore, it is very crucial to understand the price discovery and volatility spillover across the spot and future markets to hedge the financial risk and protect the interest of all stakeholders involved in agriculture markets.

Review of Literature:

Several studies have been conducted on the price trends and volatility of the spot and commodity futures markets. Debasish and Kushankur (2011) analysed the volatility in pepper and discovered bi-directional volatility spill over between futures and spot markets whereas Srinivasan (2011) found the transfer of fluctuation from spot to futures commodities markets.

Sehgal (2013) studied four commodity indexes and twelve actively traded commodities like agriculture, metals, and energy. Price discovery was observed for eight commodities and three indices, with futures markets playing a significant role. However, only three commodities showed volatility spillover effects. Gil-Alana and Tripathy (2014) evaluated the price volatility shock for seven agricultural products. They found mean reversion with shocks dissipating over time for some commodities, while for others; shocks were permanent, leading to lasting effects. The studies draw attention to how difficult it is to determine prices and how instability may spread throughout national and international commodities markets.Kumar et al., (2015) studied the price discovery in Indian commodity market and have noticed that futures and spot prices have a long-term equilibrium connection, with the futures leading the spot. Gardebroek et al., (2016) analysed how conditional correlations and volatility transfer have changed over time for maize, wheat, and soybean price returns. They also discovered a significant volatility transmission across commodities due to interconnected global markets, where volatility in one market spreads to others. The transfers of price signals and volatility repercussions between the spot and futures prices for black pepper in India were examined by Sinha et al., (2017) by applying Dynamic Conditional Correlation and VEC-BEKK models. The study concluded that the volatility of the spot market for black pepper is more persistent, primarily influenced by volatility transmission from the futures market.Chang et al., (2018), the links and interactions between the agriculture and energy industries in terms of pricing and volatility were investigated. They discovered volatility spillovers between these markets using multivariate conditional volatility diagonal BEKK models. Cinar (2018) used the BEKK version of the multivariate Generalized Autoregressive Heteroskedastic method to study volatility transmission among maize, wheat, and barley prices in Turkish markets. A single direction, considerable, and sustained transmission of volatility from the markets for corn and barley to the market for wheat was demonstrated by the BEKK MGARCH model. G. K et al., (2018) study looked into a variety of issues related to price fluctuation in the futures market and how it affected the spot market by using daily closing price data. The empirical study discovered a protracted equilibrium link among spot and futures for all commodity spices, with futures prices leading price discovery mechanism. Saghaian et al., (2018) utilized the BEKK-multivariate-GARCH method to examine asymmetric volatility spillovers between maize, oil, and ethanol prices. The findings indicated asymmetric volatility transmission between maize and ethanol prices. Sinha et al. (2018) evaluated the interdependence between onion markets in Mumbai, Nashik, Delhi, and Bengaluru in terms of price volatility. They used a VEC-MGARCH model and found volatility spillover effects across the onion markets.The volatility propagation between crude oil and agrarian commodities markets (corn, soybeans, and wheat) was addressed by Lu et al., (2019) across two time periods. A heterogeneous autoregressive (HAR) model was estimated during the crisis phase and detected bi-directional spillover instability between crude oil and agricultural commodities prices.They discovered that own- and cross-volatility shocks often outweigh one another. The price fluctuations in major pulses in India were examined by Asha Bisht et al. (2019) and found that the price system's shocks are permanent for pulses and do not gradually return to the mean. Factors like lack of supply, traders' monopolistic behavior, increased profit margins, lack of information, and inadequate infrastructure contribute to high volatility. Taghizadeh-Hesary et al., (2019) study uses a Panel-VAR model to examine the connections in food and energy costs across eight Asian countries from 2000 to 2016.Findings show that the price of energy (oil) considerably affects food prices. R L and Mishra (2020) researched the agricultural markets in India and found a bidirectional spillover effects between the futures and spot markets, which increased the efficiency of the futures market in price discovery mechanism. Gupta and Bhardwaj (2020) predict that both the spot and futures markets are equally efficient in coriander and jeera whereas the future market dominates price discovery mechanism in turmeric. Zivkov et al., (2020) analysed the long- and short-term implications of Brent oil futures on four agrarian futures. A Component GARCH model was used; the results show that the oil market's transitory influence on agricultural commodities is larger than its permanent counterpart. Kaura and Rajput, (2021) have investigated the future–spot price connection in the perspective of India's Multi Commodity Exchange's most actively traded commodities. The estimates of (VAR) model demonstrate that the futures market in India plays a less important role in agricultural commodities whereas the spot market is more prominent in price formation. Rout et al., (2021) assessed the Agro-food commodities derivative market regarding pricing volatility, hedging efficiency, and discovery, and have established that in terms of price volatility, the spot market performs better than the futures market. Pradhan (2021) examined how spot and future prices relate in the Indian commodity market by using a vector error correcting model to demonstrate the existence of Granger causality between the two markets. Statistics reveal a long-term equilibrium link between these commodities' spot and futures prices in commodities including agricultural, cattle and precious metals. Bhardwaj et al., 2022 revealed a uni-directional flow of

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volatility from Kota spot prices to future prices of soybean whereas study noticed absence of volatility transmission for Nagpur spot and Indore spot prices of soybean.

Despite several studies on commodities markets in industrialized countries, more research is needed to understand the dynamics of price discovery and volatility spillover effects, emphasizing the importance of futures markets and their influence on spot markets. But very less research has been done in India. The fundamental reason behind this is India's very recent history of organized commodities trade, which formally began in 2003 with the establishment of commodity exchanges. Very few researchers have attempted to analyze the price discovery and volatility spillover in some agricultural commodities for a short span of time with few commodities but failed to provide any convincing argument. We have noticed that no extensive empirical study has been done over the long run to investigate how prices are determined and how volatility is transmitted in the spot and futures markets of refined soy oil and RM seeds traded on NCDEX over a period of 10 years. These commodities are selected on the basis of their economic significance. The study aims to empirically investigate the price discovery process and volatility spillover in refined soy oil and RM seed. Soy oil is derived from the seeds of soybeans having a wide range of nutritional qualities and is one of India's widely consumed edible oils. India is the sixth-largest soy oil producer in the world. Next to palm oil, soybean oil is the most popular vegetable oil traded on the global markets. India is the fourth largest producer of rape seed, contributing around 11% of the world's total production. Rape seed is the second largest preferred oil seed crop in India and a vital part of Indian cuisine and is also significant in providing food security in the country.

Research Methodology

The daily average spot and futures prices of the commodities from 2011 to 2021 have been used to estimate results. The study uses Augmented Dickey-Fuller Test, Phillip Perron Test to estimate the unit root in the dataset. Johansen cointegration has been employed to find cointegration between the spot and future prices of respective commodities whereas granger causality, vector error correction model (VECM) has been used to investigate the price discovery. The ARCH model has been used to establish the presence of time varying conditional volatility and the persistence of volatility shocks in the prices. Thereafter, The Baba-Engle-Kraft Kroner version of the multivariate Generalized Autoregressive Heteroskedastic method (BEKK- MGARCH model) developed by Engle and Kroner (1995) is employed to estimate volatility spillover in spot and future prices of select commodities traded on National Commodity and Derivative Exchange (NCDEX).

Figure 1: Graphical Representation of Soy Oil

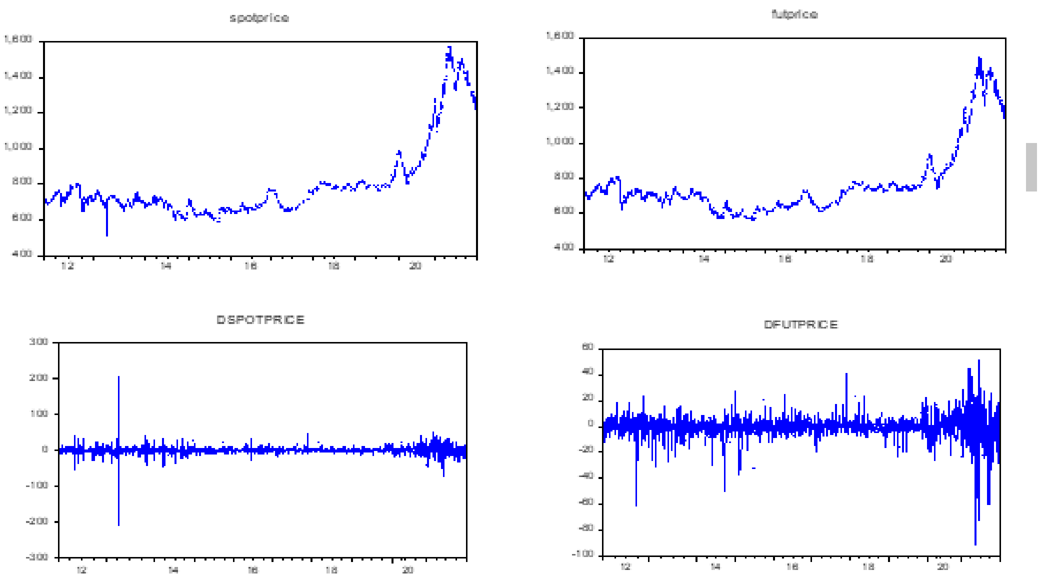

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Figure 2: Graphical Representation of RM Seed

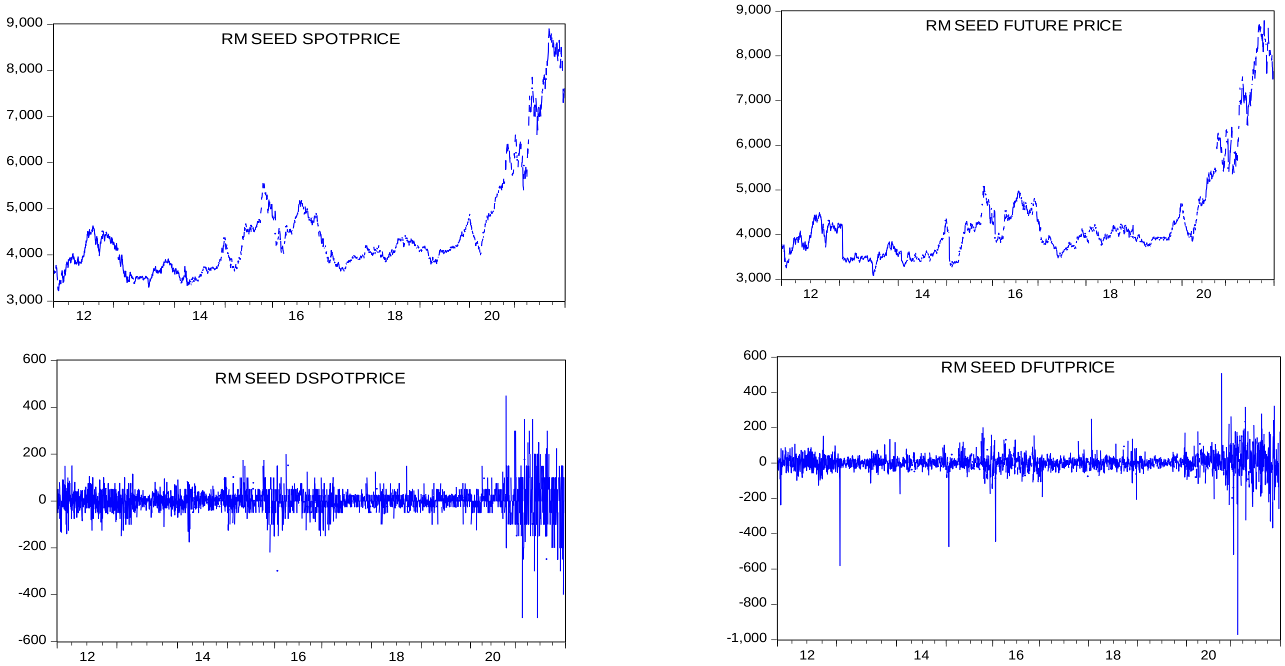

Table1: Descriptive Statistics

	Soy oil Spot price	Soy oil Future price	RM Seed Spot price	RM Seed Future price
Mean	799.7238	769.1202	4487.026	4328.892
Median	730.0000	720.5188	4150.000	3979.250
Maximum	1575.000	1495.550	8900.000	8788.750
Minimum	508.0000	563.7000	3225.000	3084.750
Std. Dev.	210.1324	194.2063	1126.607	1109.598
Skewness	2.080277	2.031521	2.085057	2.218982
Kurtosis	6.517413	6.444196	7.113638	7.613059
Jarque-Bera	3077.075	2941.107	3558.427	4249.537
Probability	0.000000	0.000000	0.000000	0.000000
Sum	1989713.	1913571.	11168209	10774611
Sum Sq. Dev.	1.10E+08	93799905	3.16E+09	3.06E+09
Observations	2488	2488	2489	2489

The descriptive statistics are the first statistical information enabling the presentation and interpretation of the data in a more meaningful manner. It is the simplest way of classifying and summarising the information thus helping in the better

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understanding of a dataset. The return series of the dataset has been used in the study for measuring central tendency, dispersion and normality and result are presented in *Table 1*. The descriptive statistics indicate that these commodity prices are positively skewed, exhibit high kurtosis, are not normally distributed (as shown by the Jarque-Bera test), and have a considerable range of values with some level of price volatility, as indicated by the standard deviation. These statistics are essential for understanding the characteristics of the commodity price data and can be valuable for risk management and decision-making in the respective markets.

Stationary Test

The Augmented Dickey-Fuller (ADF, 1979) and Phillips-Perron (PP, 1988) tests are commonly used to assess whether a time series is stationary. Stationarity is a critical concept in time series analysis because it implies that the statistical properties of a series, such as mean and variance, remain constant over time. A non-stationary series may have trends, seasonality, or other time-dependent patterns that can make modelling and forecasting more challenging.

Table 2: Estimation results of Augmented Dickey–Fuller Test

Commodities	**ADF Test**	**t-statistic**	**Critical Value**	**P-Value**
Soy Oil Spot Price	Level	-0.037651	-3.432787	0.9540
	First Difference	-58.96245	-3.432787	0.0001
Soy Oil Future Price	Level	-0.466563	-3.432787	0.8951
	First Difference	-39.99661	-3.432787	0.0000
RM Seed Spot Price	Level	-0.057123	-3.432785	0.9521
	First Difference	-47.90500	-3.432785	0.0001
RM Seed Future Price	Level	-0.244773	-3.432785	0.9303
	First Difference	-43.49649	-3.432785	0.0000

*Note: Significant at: *0.01 and **0.05 level*

The ADF test evaluates whether a time series is stationary in its original form (level) or after differencing (first difference).For Soy Oil Spot Price and Future Price: At the level (original form), the t-statistic is negative but not significant (above the critical value), with p-values well above the significance level of 0.05. This suggests non-Stationarity in the original series. After differencing (first difference), the t-statistic is highly negative and significant (well below the critical value) with p-values close to zero. This indicates that differencing the series makes them stationary. For RM Seed Spot Price and Future Price: Similar to Soy Oil, at the level, the t-statistic is not significant, indicating non-Stationarity. However, after differencing, the t-statistic is highly negative and significant, confirming Stationarity.

Table 3: Estimation results of Phillips and Perron Test

Commodities	**ADF Test**	**t-statistic**	**Critical Value**	**P-Value**
Soy Oil	Level	-0.261338	-3.432785	0.9280

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Spot Price	First Difference	-58.24498	-3.432787	0.0001
Soy Oil Future Price	Level	-0.424288	-3.432785	0.9027
	First Difference	-39.90181	-3.432787	0.0000
RM Seed Spot Price	Level	-0.231700	-3.432784	0.9320
	First Difference	-47.98818	-3.432785	0.0001
RM Seed Future Price	Level	-0.206163	-3.432784	0.9353
	First Difference	-43.47650	-3.432785	0.0000

*Note: Significant at: *0.01 and **0.05 level*

The PP test is another unit root test, and the results align closely with the ADF test. It also evaluates Stationarity in both the original series (level) and after differencing (first difference).Like the ADF test, the PP test indicates that all the commodity return series are non-stationary at the level but become stationary after differencing. This is reflected in highly negative and significant t-statistics with very low p-values after differencing.

In summary, both the ADF and PP tests provide strong evidence that the commodity return series are non-stationary in their original form (level) but become stationary after taking the first difference. Stationarity is a fundamental assumption for many time series models, so differencing the data are a common practice to make it suitable for analysis and modelling.

LONGRUN RELATIONSHIP: Johansen Cointegration Test

The Johansen Cointegration Test is used to determine whether there is a long-run relationship (cointegration) between two or more time series. In this research paper, we have applied this test to assess cointegration between different pairs of commodity prices (Soy oil Spot and Soy oil Future, RM Seed Spot and RM Seed Future).The results of the Johansen Cointegration Test are presented in Table 3. The test evaluates two hypotheses:

Null Hypothesis (R=0): There is no long-run cointegration.

Alternate Hypothesis (R=1): There is long-run cointegration

Table 3: Estimation results of Johansen Cointegration Test

Commodities	**Lags**	**H_0:R**	**Trace Statistics**		**Max-Eigen Statistics**		**Comment**
			λ trace	**Prob.**	**λ trace**	**Prob.**	
Soy oil Spot Soy oil Future	04	0	39.04207	0.0000	38.96921	0.0000	R=1 reject non-cointegration
		1	0.072855	0.7872	0.072855	0.7872	
RM Seed Spot RM Seed Future	04	0	60.15544	0.0000	60.13444	0.0000	R=1 reject non-cointegration
		1	0.021000	0.8847	0.021000	0.8847	

*Note: Significant at: *0.01 and **0.05 level*

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In Soy oil Spot and Soy oil Future: When considering up to 4 lags, both the Trace Statistics and Max-Eigen Statistics indicate highly significant p-values of 0.0000 for both cases (R=0). This means that the null hypothesis of no cointegration (R=0) is strongly rejected. The comment "R=1 reject non-cointegration" suggests that there is long-run cointegration between Soy oil Spot and Soy oil Future prices and in the case of RM Seed Spot and RM Seed Future: Similar to the Soy oil case, when considering up to 4 lags, both the Trace Statistics and Max-Eigen Statistics indicate highly significant p-values of 0.0000 for both cases (R=0). This means that the null hypothesis of no cointegration (R=0) is strongly rejected. The comment "R=1 reject non-cointegration" also suggests that there is long-run cointegration between RM Seed Spot and RM Seed Future prices. In both cases, the results strongly support the alternate hypothesis (R=1), indicating that there is indeed a long-run cointegration relationship between the spot and future prices of the respective commodities. This finding is significant because cointegration implies that these price series move together in the long run, which can have important implications for hedging and risk management in these markets.

Pair wise Granger Causality Test

The Pair-wise Granger Causality Test is used to assess whether one time series can predict or "Granger-cause" another time series. This test is valuable in understanding the direction of causality between two variables.

Commodities	Null Hypothesis:	F-Statistic	Probability
Soy Oil	DSPOTPRICE does not Granger Cause DFUTPRICE	21.6070	1.E-17
	DFUTPRICE does not Granger Cause DSPOTPRICE	78.1538	8.E-63
RM Seed	DSPOTPRICE does not Granger Cause DFUTPRICE	1.40587	0.0294
	DFUTPRICE does not Granger Cause DSPOTPRICE	24.8055	3.E-20

*Note: Significant at: *0.01 and **0.05 level*

The probability (p-value) is extremely low, thus the results suggest that there is strong evidence to reject the null hypothesis for both Soy Oil and RM Seed, the Granger causality tests indicates a bi-directional causality relationship between the spot and future prices of both the commodities under study.

Heteroscedasticity Test: ARCH Effect

Volatility transmission determines how price signals flows from one market to other causing unanticipated price variations. Before the estimation of GARCH model the data series has been analyzed for ARCH effect. If there is no ARCH effect there is no need of running GARCH model. The Heteroscedasticity Test, specifically the ARCH (Autoregressive Conditional Heteroskedasticity) Effect, is used to determine whether there is evidence of changing variance or volatility in a time series. In this research paper, this test is applied to examine the presence of an ARCH effect in the commodities price datasets (Soy Oil Spot Price, Soy Oil Future Price, RM Seed Spot Price, RM Seed Future Price).

Table 4: Estimation results of ARCH Model

Commodities	**F-statistics**	**Prob.**	**R^2**	**Prob.**
Soy Oil Spot Price	774.9524	0.0000	603.5129	0.0000
Soy Oil Future Price	58.30651	0.0000	57.12441	0.0000
RM Seed Spot Price	79.49559	0.0000	77.09334	0.0000
RM Seed Future Price	6.013281	0.0143	6.003593	0.0143

*Note: Significant at: *0.01 and **0.05 level*

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The results for Soy Oil Spot Price indicate a highly significant ARCH effect. This suggests that the dataset exhibits changing variance over time, which is dependent on its lagged effects (autocorrelation). In other words, there is evidence of volatility clustering or clustering of large and small price changes. Similarly, for Soy Oil Future Price, the results indicate a highly significant ARCH effect. This means that this dataset also shows evidence of changing variance, which depends on lagged effects. The results for RM Seed Spot Price indicate a highly significant ARCH effect, similar to Soy Oil. This suggests changing variance over time, dependent on lagged effects. For RM Seed Future Price, the results also indicate an ARCH effect. However, the significance level (p-value) is slightly higher compared to the other cases, suggesting a somewhat weaker presence of changing variance. In summary, the results suggest that there is an ARCH effect in the datasets of Soy Oil Spot Price, Soy Oil Future Price, RM Seed Spot Price, and RM Seed Future Price. This means that these datasets exhibit changing variance or volatility over time, which can be influenced by past observations. Since ARCH effects are present, it is appropriate to proceed with the application of the BEKK-GARCH model to further analyze and model the volatility in these commodity prices.

Volatility Spillover by Diagonal BEKK-GARCH Model

The BEKK GARCH Model introduced by Baba, Engle, Kraft, and Kroner in 1991, is an extension of the traditional GARCH (Generalised Autoregressive Conditional Heteroskedasticity) model used to forecast time-varying volatility in financial data series.

Table 5: Estimation results of Diagonal BEKK-GARCH Model for Refined Soy oil

Mean Equation				
	Coefficient	Std. Error	Z-Statistic	Prob.
C(1)	6.20E-05	0.000168	0.368336	0.7126
C(2)	0.182800	0.013340	13.70342	0.0000
C(3)	0.000129	0.000175	0.734043	0.4629
C(4)	0.136575	0.004680	29.18010	0.0000
Variance Equation				
	Coefficient	Std. Error	Z-Statistic	Prob.
C(5)	1.29E-06	1.46E-07	8.801896	0.0000
C(6)	7.15E-07	1.18E-07	6.056941	0.0000
C(7)	6.66E-07	7.14E-08	9.324553	0.0000
C(8)	0.153049	0.010622	14.40860	0.0000
C(9)	0.048174	0.004886	9.860501	0.0000
C(10)	0.029471	0.002414	12.21075	0.0000
C(11)	0.057956	0.015681	3.695991	0.0002
C(12)	-0.003502	0.005257	-0.666175	0.5053
C(13)	-0.013265	0.002708	-4.898053	0.0000
C(14)	0.871281	0.004617	188.7176	0.0000
C(15)	0.945240	0.004321	218.7373	0.0000
C(16)	0.971026	0.001663	583.9086	0.0000
Transformed Variance Coefficients				
	Coefficient	Std. Error	Z-Statistic	Prob.
M(1,1)	1.29E-06	1.46E-07	8.801896	0.0000
M(1,2)	7.15E-07	1.18E-07	6.056941	0.0000
M(2,2)	6.66E-07	7.14E-08	9.324553	0.0000
A1(1,1)	0.153049	0.010622	14.40860	0.0000
A1(1,2)	0.048174	0.004886	9.860501	0.0000
A1(2,2)	0.029471	0.002414	12.21075	0.0000

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D1(1,1)	0.057956	0.015681	3.695991	0.0002
D1(1,2)	-0.003502	0.005257	-0.666175	0.5053
D1(2,2)	-0.013265	0.002708	-4.898053	0.0000
B1(1,1)	0.871281	0.004617	188.7176	0.0000
B1(1,2)	0.945240	0.004321	218.7373	0.0000
B1(2,2)	0.971026	0.001663	583.9086	0.0000

*Note: Significant at: *0.01 and **0.05 level*

The results of the Diagonal BEKK-GARCH model for Refined Soy Oil provide insights into the dynamics of volatility and the spillover effects in the commodity's price. The model contains both a mean equation and a variance equation, which help us understand how volatility is determined and transmitted. The coefficients C(1) to C(4) in the mean equation suggests that lagged values of the mean have a significant positive impact on the mean of Refined Soy Oil prices. The coefficients C(5) to C(16) in the variance equation correspond to various lagged terms that affect the conditional variance of Refined Soy Oil prices. All of these coefficients are highly statistically significant ($p = 0.0000$), indicating that past observations significantly impact the conditional variance. Transformed Variance Coefficients represent the relationships between lagged squared returns and the conditional variance. All of them are highly statistically significant ($p = 0.0000$), suggesting that past squared returns are significant determinants of the conditional variance. A1(1.1), (1,2), (2,2) signifies that Impact of news in one market is effecting the conditional co-variance of two markets. B1(1,1), (1,2), (2,2) signifies the persistence level in both markets is also causing the co-variance in both the markets. M1(1,2),(2,1),(2,2) signifies there is a long term co variance between the two markets. D1(1,1) represents whether the effect of 1st market is asymmetric or not, D1(1,1) is found to be asymmetric.D1(2,2) is also found to be asymmetric it means negative shocks in one market increases the covariance between the two markets.

In summary, the Diagonal BEKK-GARCH model results for Refined Soy Oil indicate that the mean of prices is influenced by lagged values of the mean, with significant positive effects. Additionally, the conditional variance is significantly affected by lagged squared returns, indicating the presence of volatility clustering. This means that periods of high volatility tend to cluster together. The results also imply that there is evidence of volatility spillover in Refined Soy Oil prices, as past returns affect future volatility.

Table 6: Estimation results ofDiagonal BEKK-GARCH Model for RM Seed

Mean Equation				
	Coefficient	Std. Error	Z-Statistic	Prob.
C(1)	131.6545	6.057767	21.73317	0.0000
C(2)	1.000362	0.001323	756.0844	0.0000
C(3)	25.58657	7.138425	3.584343	0.0003
C(4)	0.960962	0.001605	598.6288	0.0000
Variance Equation				
	Coefficient	Std. Error	Z-Statistic	Prob.
C(5)	338.7788	37.52936	9.027033	0.0000
C(6)	-96.00127	23.70513	-4.049810	0.0001
C(7)	224.1029	28.96427	7.737219	0.0000
C(8)	0.549259	0.015426	35.60576	0.0000
C(9)	0.492840	0.012649	38.96201	0.0000
C(10)	0.113418	0.017353	6.535926	0.0000
C(11)	-0.016533	0.049210	-0.335975	0.7369
C(12)	0.837597	0.006656	125.8354	0.0000
C(13)	0.873536	0.004345	201.0430	0.0000
Transformed Variance Coefficients				

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	Coefficient	Std. Error	Z-Statistic	Prob.
M(1,1)	338.7788	37.52936	9.027033	0.0000
M(1,2)	-96.00127	23.70513	-4.049810	0.0001
M(2,2)	224.1029	28.96427	7.737219	0.0000
A1(1,1)	0.549259	0.015426	35.60576	0.0000
A1(2,2)	0.492840	0.012649	38.96201	0.0000
D1(1,1)	0.113418	0.017353	6.535926	0.0000
D1(2,2)	-0.016533	0.049210	-0.335975	0.7369
B1(1,1)	0.837597	0.006656	125.8354	0.0000
B1(2,2)	0.873536	0.004345	201.0430	0.0000

*Note: Significant at: *0.01 and **0.05 level*

The results of the Diagonal BEKK-GARCH model for RM Seed provide insights into the volatility dynamics and spillover effects in the commodity's price. The coefficient in the mean equation is highly statistically significant implying that lagged values of the mean have a significant positive effect on the mean of RM Seed prices. The coefficients C(5) to C(12) in the variance equation correspond to various lagged terms that affect the conditional variance of RM Seed prices. All of these coefficients are highly statistically significant (p = 0.0000), indicating that past observations significantly impact the conditional variance. Transformed Variance Coefficients represent the relationships between lagged squared returns and the conditional variance. All of them are highly statistically significant (p = 0.0000), suggesting that past squared returns are significant determinants of the conditional variance. In summary, the Diagonal BEKK-GARCH model results for RM Seed indicate that the mean of prices is influenced by lagged values of the mean, with significant positive effects. Additionally, the conditional variance is significantly affected by lagged squared returns, indicating the presence of volatility clustering. This means that periods of high volatility tend to cluster together. The results also imply that there is evidence of volatility spillover in RM Seed prices, as past returns affect future volatility.

Findings

The study uses Augmented Dickey-Fuller Test (ADF) and Phillip Perron Test (PP) to find out unit root in the spot and future prices of commodities taken for the study. The t-statistics and P-value of both the tests show that the prices of commodities are not stationary at level, which means there is an integration of order (1). That is, stationary at first difference. The estimates of Johansen cointegration test predict that the spot and future prices of refined soy oil and RM seed are cointegration. Test results of both Trace Statistic (λ trace) and Max-Eigen Statistic (λ max) are more than the critical value and p-value is less than 5% significance level which rejects the null hypothesis (R=0) of cointegration. The results of granger causality, vector error correction model (VECM) show that price discovery takes place in both the markets and markets are found to be equally efficient in adjusting the new information in the equilibrium price. Volatility clustering is the important stylized facts of financial time series. Graphical representation of the dataset shows that small changes are followed by small changes and large changes are followed by large changes in the prices of commodities taken for study.Volatility transmission determines how price signals flow from one market to another, causing unanticipated price variations. Before the estimation of BEKK-GARCH model the data series was analyzed for ARCH effect. The values of F-stat, R^2 and Probability show that the soy oil and RM seed dataset has heteroscedasticity which depends on its lagged effects (autocorrelation).The ARCH model has been used to establish the presence of time varying conditional volatility and persistence of volatility shocks, confirming the presence of ARCH effect satisfying the precondition for using GARCH model. The study has employed BEKK-GARCH model for estimating volatility spillover. The results of the model show that all the parameters of mean and variance equations are significant for ref. soy oil and RM seed, confirming a volatility spillover effect. It has been noted that A1(1.1),(1,2),(2,2) is significant, which predicts the impact of news in one market is effecting the conditional covariance of two markets. Whereas B1(1,1),(1,2),(2,2) is significant, confirming persistence level in both markets is also causing the co-variance in both the markets. The parameters of asymmetric terms D(1,1), (2,2) are also significant, meaning that negative shocks in one market increase the co-variance in both markets in the commodities under study. The result predicts a significant volatility spillover between the spot and future prices of refined soy oil and RM seed.

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Conclusion

Agricultural commodity exchanges offer a centralised setting where farmers and market players may transfer commodity price risk and determine the cost of future deliveries. For these futures markets to remain viable, efficient pricing, flexible contract design, management of risks, regulation of unfair speculation, delivery system, market infrastructure, and other elements are required. These markets also need to be efficient and transparent. The study adds to the existing body of knowledge by examining the causal link, cointegration, price discovery, and volatility spill over in the spot and futures markets for refined soy oil and RM seed, traded on National Commodity and Derivative Exchange of India. The cointegration test revealed that spot and futures prices for the commodities had long-term equilibrium linkages. The results of granger causality show that price discovery takes place in both the markets which are found to be equally efficient in adjusting the new information in the equilibrium price. The diagonal BEKK-GARCH model demonstrate that all the parameters of the mean and variance equations are significant, revealing the existence of a volatility spill over effect between the spot and future prices of both the markets of refined soy oil and RM seed. Due to market interaction and information flow reflected in the spot and futures markets, price discovery and spill over effects are clearly visible in both the markets. Producers, consumers as well as other stakeholders can formulate pricing plans and market investment strategies to hedge their price risk. To help farmers and traders with more authentic information, policymakers and regulators should emphasise the transparency and efficiency of markets by increasing market participation by putting in place suitable trading and hedging techniques.

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