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RESEARCH ARTICLE

Price Patterns in Agricultural Futures Markets: A GARCH Model Approach

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ABSTRACT

The outbreak of corona virus has affected the financial market internationally in an unprecedented way. Due to the devastations that emerged in the international market, the Indian financial market proportionally reacted to the pandemic and further witnessed violent volatility. Considering the COVID-19 situation, this paper is an empirical investigation on the impact of COVID-19 on agricultural commodities, specifically on NCDEX platform. Using daily closing future prices of guar seed, jeera, turmeric, and Coriander on NCDEX, this study examines the impact of COVID-19 on the selected commodities over the period from 24th December 2019 to 24th June 2020, representing three months before and during the covid – 19 spread. This study has tried to compare the future prices in the pre-COVID-19 period and during the COVID-19 situation, by using GARCH Model. Findings reveal that the price of jeera, turmeric and coriander has encountered instability during the Corona pandemic period.

Keywords: *Agricultural Futures; NCDEX; Covid – 19 and GARCH Model.*

INTRODUCTION

Commodities have been the bedrock of civilization and have determined the fate and fortune of nations and would continue to do so in future because of the volatility prevailing in their markets (Dasgupta and Chakrabarty 2009). Therefore, price volatility drives the demand for hedging the risk in the commodity market. Typically, supply shocks were the primary cause of price volatility in agricultural commodities. Price fluctuations were caused by the disruptions in combination with the short-run demand and supply elasticity factors. Commodity markets have often shown that the key variables influencing price volatility were information flow about pricing, hedging and speculation, and physical availability of commodities. Speculation was now widespread in commodity markets due to the rising price volatility of essential agricultural goods. This characteristic can support the application of information-based modeling techniques to simulate price volatility (Vasisht and Bhardwaj, 2010).

The globe was in danger due to the coronavirus's unprecedented epidemic, which had also unpredictably altered the global landscape. The COVID-19 pandemic was started by the SARS-CoV-2 virus, which first appeared in December 2019 in Wuhan, China, and quickly spread like wildfire over the world. Not only this widespread viral outbreak a worldwide health emergency, but it was also a crucial turning point for the world economy. To combat the epidemic, several nations have resorted to adopting tight quarantine rules, which have severely slowed down their economies (Kumar and Reddy, 2020). Countries were restricting or banning international travel, slowing down the world economy even further. Most crucially, businesses and consumers have reduced their purchasing patterns, further exacerbating market irregularity. The pandemic's unpredictability and riskiness had a significant economic impact on both developed and emerging countries, including those of the US, Spain, Italy, Brazil, and India. The Indian commodities market has responded with spectacular movement against this background and is negatively impacted. The government's lockdown tactics forced the closure of the mandis and factories, further impeding price discovery and output levels, which had an impact on the supply chain. Another significant effect was a demand shock brought on by lower consumption. The significant effects had on the commodities markets of the Indian economy. This paper attempts to find the impact of COVID-19 on one of the agricultural commodities on NCDEX, the major commodity market of India. GARCH Model is used to examine the volatility in guar seed, jeera, turmeric and coriander future prices before and during the COVID-19 pandemic.

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MATERIAL AND METHODS

In general, any price series exhibit a tendency of volatility clustering i.e., periods of high and low market uncertainty. Specifically, agricultural commodity prices require modeling within a flexible and unified framework. Despite the fact that several models exist to capture the volatility in price series, the vanilla Generalized Autoregressive Conditional Heteroscedasticity (GARCH) was used to measure the extent of volatility in agricultural commodity prices due to futures trading owing to its popularity and wide application by the economists and policy makers (Lee 1991). Bollerslev (1986) generalized the Engel's ARCH model, which distinguishes not only between predictable and unpredictable components of prices but also allows the variance of the unpredictable element to be time varying. Evidence of ARCH and GARCH is widespread in series that are partly driven by speculative forces. However, these may also be present in the behavior of agricultural commodity prices with an expected positive transmission of volatility across commodities. Hence it takes the choice of a widely used model in estimating the volatility in agricultural commodity prices.

Hitherto, the use of GARCH models in capturing the agricultural commodity price volatility has been limited in India, unlike analysing the financial instruments. However, Mahalik et al. (2009), Vasisht and Bhardwaj (2010), Mahesha (2011), Sundaramoorthy et al. (2014) and a few others analyzed the volatility in agricultural commodities.

The commonly used GARCH (1,1) model is defined below.

$$Y_{it} = a_0 + b_1 Y_{it-1} + b_2 Y_{it-2} + \varepsilon_{it} \quad (1)$$

Where Y_{it} is future price of i^{th} commodity in t^{th} period and t is the time period ranging from 1,2,3 ... n. The variance of the random error is given as

$$\sigma^2_{i,t} = \omega + \alpha_i \varepsilon^2_{i,t-i} + \beta_i \sigma^2_{i,t-i} \quad (2)$$

The conditional variance equation specified in the above equation is a function of three terms viz., the mean (☐), news about volatility from the previous period measured as the lag of the squared residual from the mean equation (ε^2_{t-1}, the ARCH term) and the last period's forecast variance (σ^2_{t-1}, the GARCH term). The (1, 1) in GARCH (1, 1) refers to the presence of a first-order GARCH term (the first term in parentheses) and a first-order ARCH term (the second term in parentheses). The sum of (αi + βi) gives the degree of persistence of volatility in the price series. The closer the sum to one, the greater the tendency of price volatility to persist for a long time. If the sum exceeds one, it indicates an explosive time series that tends to meander away from the mean value. The mean term (ω) given in equation (2) is written as a function of exogenous variables with an error term. Since σ^2_t is the one-period ahead forecast variance based on past information. It is called conditional variance.

An ordinary ARCH model is a special case of a GARCH specification in which there are no lagged forecast variances in the conditional variance equation. Higher order GARCH models, denoted by GARCH (p, q), can be estimated by choosing either p or q or both greater than one. The representation of the GARCH (p, q) is given as,

$$\sigma^2_{i,t} = \omega + \sum_{i=1}^{p} \beta_i \sigma^2_{t-i} + \sum_{i=1}^{q} \alpha_i \varepsilon^2_{t-i} \quad (3)$$

where, p is the order of the GARCH terms and q is the order of the ARCH term.

After fitting the model, it was tested for ARCH- LM (ARCH-Lagrange Multiplier test) to identify whether the fitted model has any further ARCH effect i.e., testing white noise disturbances against GARCH disturbances in the linear regression model (Lee 1991). In plain term, ARCH-LM is the test for identifying the presence of serial correlation in the residuals of the fitted GARCH/ARCH series of models. The best fitted model with no further ARCH effects was presented and discussed further. EVIEWS 7 software has been used for estimating the GARCH/ARCH set of models.

RESULTS AND DISCUSSION

The data are analyzed, and results are presented in Tables 1 & 2. The table 1 and 2 narrate the summary statistics of the selected NCDEX Agricultural commodities for pre and during Covid – 19 pandemic. While pre Covid – 19 pandemic period, coriander had higher standard deviation and high return among the selected commodities. During Covid – 19 pandemic, guar seed showed higher standard deviation and high return. Fig 1 explains the trend of the return for selected commodities.

Table 1 Summary Statistics for Future return during Pre Covid – 19 Pandemic Period

Asset	Observation	Mean	Std dev	Min	Max
Guar seed	64	-0.420	1.755	-4.442	3.751
Jeera	64	-0.364	2.104	-11.152	3.919
Turmeric	64	-0.110	2.312	-6.203	7.855
Coriander	64	-0.148	**2.344**	-4.393	9.464

Table 2. Summary Statistics for Future return During Covid – 19 Pandemic Period

Asset	Observation	Mean	Std dev	Min	Max
Guar seed	64	0.185	**2.162**	-6.014	5.016
Jeera	64	0.012	1.317	-4.275	3.189
Turmeric	64	0.009	1.527	-4.082	3.385
Coriander	64	0.108	1.815	-3.609	3.763

The study first estimates the univariate GARCH (1,1) processes and reports the results for mean and variance equations of the GARCH model estimations. The first step to check whether the stability conditions of the GARCH model are satisfied or not by imposing the constraints ω> 0, 0≤ α, 0≤β, α+β<1. The GARCH model satisfies the stability conditions, therefore, the researcher proceed to draw some inferences. The Table 3 and 4 revealed GARCH estimates for pre and during period of Covid – 19 pandemic. Among agriculture commodities class, pre period of Covid – 19 pandemic, coriander showed significant negative α and positive β coefficients with extremely high volatility; turmeric observed a significant positive β coefficient with very high volatility. During the Covid – 19 pandemic, jeera, turmeric and coriander showed significant positive α and positive β coefficient with extremely high volatility.

Table 3. GARCH Estimates for NCDEX Commodities in Pre Covid – 19 Pandemic

Variables	Pre Covid - 19 Pandemic				
	ω	α	β	α+β	Volatility
AGRICULTURAL CLASS					
Guar seed	0.73	0.42	0.25	NS	-
Jeera	0.03	-0.10	1.15	NS	-
Turmeric	0.41	-0.02	0.89***	0.89	Very High
Coriander	-0.03	-0.12***	1.16***	1.04	Extremely High

Source: Researcher's Computation

*Notes: ***, ** and * denotes 1%, 5% and 10% level of significance; NS – Not Significant*

Table 4 . GARCH Estimates for NCDEX Commodities During Covid – 19 Pandemic

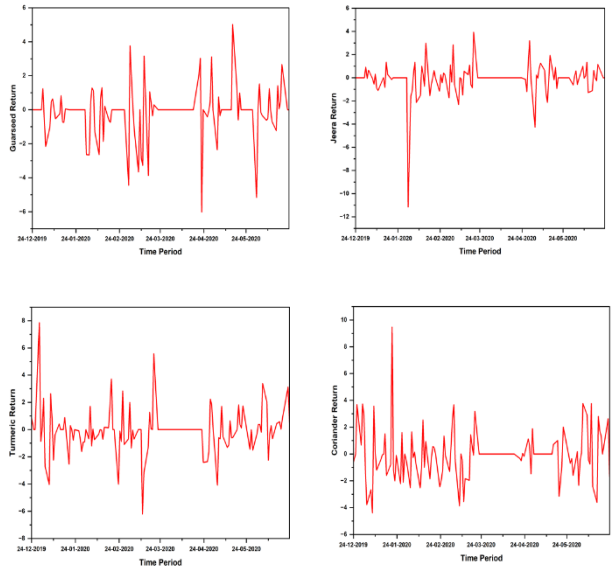
Variables	During Covid - 19 Pandemic				
	ω	α	β	α+β	Volatility
AGRICULTURAL CLASS					
Guar seed	1.085	-0.062	0.592	NS	-
Jeera	0.001***	3.007***	0.414***	3.42	Extremely High
Turmeric	0.033***	0.087***	0.934***	1.02	Extremely High
Coriander	0.002***	0.768***	0.689***	1.45	Extremely High

Source: Researcher's Computation

*Notes: ***, ** and * denotes 1%, 5% and 10% level of significance; NS – Not Significant*

Guar seed's volatility remained unchanged during the pandemic, the extremely high volatility of jeera during the pandemic indicates significant market disruptions. The high β value suggests that jeera was heavily influenced by broader market trends. A higher beta value implies that past conditional variances have a stronger influence on the current volatility, indicating that the volatility changes are more persistent over time. Turmeric's very high volatility indicates market sensitivity. The shifts in α and β during the pandemic suggest changes in its performance dynamics. Coriander's extremely high volatility before and during the pandemic highlights its sensitivity to market conditions. The significant changes in α and β during the pandemic could be due to disruptions in supply or shifts in demand.

Fig 1 Trend of the Return for selected commodities



Conclusion

Volatility is a significant supply-related risk factor, particularly for agricultural commodities. Due to its biological nature and seasonal output, agriculture experiences more extreme price swings than any other sector of the economy. The degree of price volatility in the future's market was quantified using the GARCH model. The results indicated shifts in volatility from pre to during Covid-19 pandemic period. The present study concludes that futures trading could be a reason for the reduction in price volatility but certainly not in all commodities. Agricultural price volatility is primarily caused by supply shocks. The extent of the volatility is determined by the variances of these shocks and the elasticity coefficients of the supply and demand functions (Sendhil *et al.,* 2014). Those who claim that price volatility will be higher over a long period must either believe that shock variances have increased or that the elasticity coefficients of demand and supply functions have declined. Despite these complexities, the study recommends that the commodity exchanges established at the national and regional level should continue trading in commodities with low volatility. For the rest of highly volatile commodity prices, the actual economic reasons for the persistence of volatility must be probed and argued coherently. Overall, the pandemic significantly impacted market volatility and asset behavior. It's important to consider the unique factors influencing each asset, to be informed about market trends, and adjust your investment and risk management strategies accordingly.

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Ethics statement

No specific permits were required for the described field studies because no human or animal subjects were involved in this research.

Originality and plagiarism

Authors should ensure that they have written and submit only entirely original works, and if they have used the work and/or words of others, that this has been appropriately cited. Plagiarism in all its forms constitutes unethical publishing behavior and is unacceptable.

Consent for publication

All the authors agreed to publish the content.

Competing interests

There were no conflict of interest in the publication of this content

Data availability

All the data of this manuscript are included in the MS. No separate external data source is required. If anything is required from the MS, certainly, this will be extended by communicating with the corresponding author through corresponding official mail..

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