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IMPACT OF COVID-19 ON THE VOLATILITY OF SELECTED COMMODITY FUTURES

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Abstract:

The aim of the study is to analyze the effect of covid-19 on the volatility of commodity futures contracts traded in MCX. The commodities are selected on the basis of high trading volume and the study considered daily closing prices of four commodities namely, Aluminum, Gold, Cotton and Crude oil during the period 1st January 2008 till 31st August 2022. The present study employed ARMA-EGARCH model for analysis. The study revealed mixed effect on the selected commodities, (i.e.) Aluminum and Crude are significant and Cotton and Gold are insignificant.

Key Words: Covid-19, ARMA-EGARCH, Volatility, MCX

Introduction:

When COVID-19 spread to 110 nations and 118,000 cases were reported, the World Health Organization proclaimed it a worldwide emergency in February 2020 and a pandemic on March 11. (WHO, 2020). Since the coronavirus pandemic, the world's economy and commodity markets have experienced a significant decline greater than the 2008 financial crisis (Yakubu and Sarkodie, 2021). Most commodity prices were significantly affected by the global economic shock following the COVID-19 pandemic's emergence, and it was anticipated that this shock would continue in 2020 albeit at somewhat slower rates (WorldBank, 2020c)

Volatility forecasting for commodity futures is critical in a variety of activities such as hedging, trading, and regulation (Ding et al., 2019; Ding et al., 2020). Commodity price fluctuations and shocks are major risks for companies with global supply chains. Commodity options are frequently used by commodity traders to hedge commodity futures price risks. Volatility forecasting is essential for accurately predicting commodity option prices because underlying futures volatility dynamics drive price movements. Commodity price shocks have an impact on people's lives as well, because commodity prices are closely linked to the consumer price index (CPI). As a result, commodity futures volatility forecasting can assist regulators in developing effective inflation control measures.

Nearly every element of the world economy has been damaged by the COVID-19 pandemic, particularly supply chain disruptions and supply-demand mismatches, which have a dramatic influence on commodities futures markets and might result in negative oil futures prices in the spring of 2020. Numerous researches have been conducted on the effect of the pandemic on

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financial markets since COVID-19 spread globally. According to Zhang and Hamori (2021), the 2008 global financial crisis was not as substantial as the long-term COVID-19 effects on the oil and stock markets. COVID-19 has increased volatility spillover effects between the stock and energy markets, according to a number of researches (Cui et al., 2021; Si et al., 2021; Liao et al., 2021).

In summary, previous research has focused on the impact of COVID-19 on stock market volatility. The impact on commodity futures volatility has not been thoroughly researched. The goal of this paper is to investigate the effects of COVID-19 on the volatility of commodity futures by developing volatility forecasting models that account for the pandemic effect.

Review of Literature:

Researchers looked into how the COVID-19 epidemic will affect the price of natural gas and crude oil in the future (Aloui et al., 2020). Gold can be used to hedge against risks from crude oil and financial markets during pandemics, according to an evaluation of its potential for doing so against risks from the oil price and stock market (Adekoya et al., 2020). The study of the relationship between commodity and financial variables in a changing regime environment revealed that there are regime-dependent interactions between variables, with duration likelihood being larger for low variance states than high variance states (Bhar and Hammoudeh 2011).

Evidence from a time-varying parameter-based study suggests that the first wave of COVID-19 significantly increased commodity return volatility (Adekoya et al., 2021). Investor uncertainty caused by the COVID-19 pandemic is said to be increasing commodity price movement (Salisu et al., 2020) Several studies have found evidence of gold's hedging potential and safe-haven status during the COVID-19 pandemic (Conlon and McGee, 2020; Sharif et al., 2020).

According to reports, the pandemic simultaneously shook supply and demand, impacting worldwide trade and upsetting the global supply chain (Baldwin and Tomiura, 2020). The results demonstrate that the COVID-19 pandemic has a major impact on how fragile the global economy is, similar to the financial crisis of 2008. (Corbet et al., 2020). Average commodity price correlation grew from 14.8% before the financial crisis to 47.9% after the 2008 financial crisis (Zhang and Broadstock, 2018).

Because of the COVID-19 pandemic's effects on worldwide economic activity, the price and demand for crude oil abruptly fell (Rajput et al., 2020). There is a considerable relationship between other markets and the commodities market (Zhang and Broadstock, 2018). Using GARCH models, a study looked at the impact of various types of speculation on the volatility of the prices of chosen commodity futures (Manera et al, 2013) An investigation on the relationship between abnormalities in the crude oil price and stock market returns in the Indian stock market from 2009 to 2018 was conducted (Hawaldar et al., 2020)

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Data and Methodology:

The volatility equation will contain COVID-19 variables under the EGARCH (p,q) framework, and ARMA(m,n) describes the mean equation for futures returns in the ARMA(m,n)-EGARCH(p,q) model. Let D serve as a dummy variable. From January 1, 2018 to August 31, 2022, we took into account the closing prices for four commodity futures: gold, aluminum, crude oil, and cotton. We choose March 12, 2020, the day the WHO announced the COVID-19 pandemic to begin. The dummy variable D will have values of 0 before this date and 1 after it.

We chose these four commodities for our investigation into futures volatility for two reasons. First, they have the most experience trading on exchanges, which helps them avoid the issue of extremely high price volatility. Second, they reflect the four commodity classes—bullion, base metals, energy, and agricultural classes—with the most actively traded (highest trading volumes) futures.

Data Analysis:

Table 1: Descriptive statistics of daily returns for selected commodity futures.

Futures Varities	Mean	S.D	Skewness	Kurtosis	Jarque-Bera	Probability
Aluminum	0.000129	0.005952	0.062902	10.81051	3048.451	0.0000
Cotton	0.000322	0.005887	-2.915758	50.49917	114127.2	0.0000
Crude Oil	0.000229	0.014596	-0.887322	30.07325	36744.17	0.0000
Gold	0.000197	0.003617	-0.729025	7.43674	1089.62	0.0000

Table 1 depicts the descriptive statistics of daily returns for four commodity futures, displaying thin peak and thick tail distribution. All the commodity futures have leptokurtic nature and three commodities are left hand tailed and one is right hand tailed. Jarque-Bera statistics accepts null hypothesis. We further conduct ADF stationarity tests for these four futures return series. Since all ADF values are less than 5% critical values, as shown in Table 2, all return series are stationary processes, necessary for subsequent model building.

Table2: ADF stationarity tests for selected futures return series

Futures Varities	ADF value	Critical Value 1%	5%	10%	Probability
Aluminum	-15.81107	-3.435673	-2.863778	-2.568012	0.0000
Cotton	-14.69940	-3.435705	-2.863793	-2.568020	0.0000
Crude Oil	-13.41590	-3.435687	-2.863784	-2.568015	0.0000
Gold	-19.74515	-3.435645	-2.863766	-2.568005	0.0000

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Table3: AC and PAC functions for Aluminum futures:

AC	PAC	Q-Stat	Prob
0.131	0.131	20.530	0.000
0.084	0.068	29.018	0.000
0.128	0.111	48.643	0.000
0.102	0.071	61.178	0.000
0.094	0.061	71.777	0.000
0.045	0.005	74.196	0.000
0.091	0.061	84.143	0.000
0.044	0.003	86.525	0.000
0.089	0.063	96.114	0.000
0.064	0.024	101.05	0.000
0.063	0.031	105.85	0.000
0.023	-0.019	106.50	0.000
0.028	0.001	107.47	0.000
0.021	-0.013	107.98	0.000
0.027	0.010	108.88	0.000
0.017	-0.007	109.22	0.000
0.017	0.004	109.55	0.000
0.018	-0.001	109.94	0.000
0.016	0.004	110.24	0.000

Table4: Heteroskedasticity Test: ARCH

	F-statistic	**Obs*R-squared**	**Prob. F(1,1196)**	**Prob.Chi-Square(1)**
Aluminum	20.78347	20.46264	0.0000	0.0000
Cotton	0.588951	0.589648	0.4430	0.4426
Crude oil	183.2288	159.1353	0.0000	0.0000
Gold	10.76853	10.69028	0.0011	0.0011

First, we calculate the ARMA (m, n) model for the mean equation. For the return time series, lag numbers m and n are determined using autocorrelations (AC) and partial autocorrelations (PAC). SIC criteria are used to determine the best fitted model. After determining the mean equation, ARMA (m, n), we test the ARCH effect for the residuals εt. Only if εt exhibits the ARCH effect could the variance equation EGARCH (p, q) be determined. The EGARCH (p, q) model is determined in the same way as the ARMA (m, n) model by combining AC and PAC functions with SIC criteria.

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Table5: Results of the ARMA-EGARCH model for Aluminum

	Variable	Coefficient	Std. Error	z-Statistic	Probability
Mean Equation	C	1.78E-05	0.000223	0.079851	0.9364
	MA(3)	-0.036584	0.030738	-1.190196	0.2340
Variance Equation	C	-0.502818	0.072631	-6.922881	0.0000
	RESID (-1) ^2	0.063200	0.012829	4.926363	0.0000
	D	-0.007006	0.006198	-1.130246	0.0424

Table6: Results of the ARMA-EGARCH model for Cotton

	Variable	Coefficient	Std. Error	z-Statistic	Probability
Mean Equation	C	6.21E-05	0.000149	0.416084	0.6773
	AR(5)	0.704875	0.081609	8.637216	0.0000
	MA(5)	-0.71339	0.083295	-8.56461	0.0000
Variance Equation	C	-1.089436	0.163534	-6.661847	0.0000
	RESID (-1) ^2	0.039037	0.017631	2.214140	0.0268
	D	0.014295	0.011620	1.230212	0.2186

Table7: Results of the ARMA-EGARCH model for Crude Oil

	Variable	Coefficient	Std. Error	z-Statistic	Probability
Mean Equation	C	-6.62E-05	0.000362	-0.183117	0.8547
	MA(4)	0.021393	0.029076	0.735769	0.4619
Variance Equation	C	-1.089436	0.163534	-6.661847	0.0000
	RESID (-1) ^2	-0.119091	0.012422	-9.586969	0.0000
	D	-0.001439	0.008599	-0.167374	0.0271

Table8: Results of the ARMA-EGARCH model for Gold

	Variable	Coefficient	Std. Error	z-Statistic	Probability
Mean Equation	C	0.000301	0.000115	2.626866	0.0086
	MA(4)	-0.036584	0.030738	-1.190196	0.2340
Variance Equation	C	-0.392749	0.091214	-4.305807	0.0000
	RESID (-1) ^2	0.074920	0.011184	6.698624	0.0000
	D	0.008249	0.006589	1.251866	0.2106

Then, we constructed the COVID-19 adjusted EGARCH (p, q) model. Using the AC and PAC functions in conjunction with SIC, we determine that the best-fitted model for the variance Equation. From the analysis, it is inferred that Aluminum and Crude oil are noteworthy as P-value of the dummy variable was below 5% significance level and Cotton and Gold are insignificant, as the P- value was above 5% critical level.

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Conclusion:

The current study explores the effect of the COVID-19 on the volatility of four major commodity futures, namely Aluminum, Cotton, Crude oil and Gold, which represent the most traded futures in their different commodity classes. Our research is carried out by extending ARMA (m, n)-EGARCH (p, q) models to incorporate COVID-19 influencing variables. The study revealed mixed Effect on the volatility of different commodity futures could be because different classes of commodities have different purposes of usages, supply and demand natures, and government measures for price stabilization, all of which result in their different responses and sensitivities to supply chain disruption risk from pandemic lockdowns.

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