Volatility Modeling of Commodity Markets in India : Application of Selected GARCH Models

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Abstract

The study focused on volatility modeling of commodity market in India based on the closing returns of indices of multi commodity exchange, that is, MCX AGRI, MCX METAL, MCX ENERGY, and MCX COMDEX during the period from April 1, 2013 to March 31, 2018. The study used symmetric and asymmetric models of auto regressive conditional heteroskedasticity (ARCH) family models. The study found significant high volatility persistence in all commodity indices of MCX. The asymmetric models of GARCH revealed a presence of leverage effect only in MCX ENERGY index and not in any other indices of MCX. Finally, AIC and SIC criteria were used to identify the best models that better described the volatility of the commodity market as the AIC and SIC values were the lowest in the most appropriate model. It was found that EGARCH (1, 1) model best fitted among all other models for MCX AGRI and MCX ENERGY ; for MCX Metal, TARCH (1,1) model was found to be the best fit; and for MCX COMDEX, GARCH(1, 1) model best described the volatility.

Keywords: **ARCH, commodity indices, EGARCH, GARCH, GARCH M, heteroskedasticity, TGARCH, volatility**

JEL Classification: C22, C32, C53, C58

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Volatility refers to the measurement of risk involved in any investment. In a broader sense, it is considered as the measurement of variability of prices of an asset over a period of time. A higher value of volatility implies that the value of the asset has been spread out over a wide range of values. A lower volatility implies that the asset's value has not fluctuated much over a period of time. Over a period of time, volatility modeling has gained attention of investors and researchers, which have helped to predict the volatility accurately. The data in the time series are found to be dependent on its own past value (autoregressive), based on past information (conditional), and exhibit non constant variance (heteroskedasticity) (Banumathy & Azhagaiah, 2014). The commodity market volatility is found to be changing over time (i.e. time varying) and is also found to exhibit volatility clustering. Volatility clustering refers to the phenomena in which low volatility is followed by periods of low volatility and periods of high volatility is followed by periods of high volatility.

Before deciding an investment, investors analyze the historical volatility to analyze the degree of risk involved in the investment. Standard deviation or variance is often used by investors to reflect how much the price of the asset has fluctuated from mean price over a period of time. Engle (1982) introduced the auto regressive conditional heteroskedasticity models to model the time series exhibiting time varying conditional variance. Bollerslev (1986) introduced generalized auto regressive conditional heteroskedasticity (GARCH) models to

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model time series exhibiting stochastic volatility. GARCH in the mean model (GARCH-M) developed by Engle and Granger (1987), which is used to capture the risk - return relationship in the time series. Since GARCH models cannot account for modeling leverage effect, and also with the restriction of non negativity of coefficients, Nelson (1991) developed exponential generalized auto regressive conditional heteroskedasticity (EGARCH) which captures the asymmetric effects of the time series using logarithmic expression of conditional volatility. Later, a number of extensions of this model were developed. One of them is the threshold GARCH model, which captures the relation between asymmetric volatility and returns. The TGARCH model is also called GJR GARCH model (Glosten, Jagannathan, & Runkle, 1993).

All the models are designed to accurately model the volatility of the markets. Hence, this paper attempts at modeling the volatility of commodity markets using various Arch family models.

Review of Literature

Amudha and Muthukamu (2018) studied the heteroskedastic pattern of Indian equity market using the GARCH family models to study the asymmetric volatility pattern of automobile stocks in NSE. The study was done during the period from April 2003 to September 2015, where the stock market showed three bull and bear phases. The study revealed a presence of clustering and persistence of volatility. It was also revealed that negative shocks demonstrated more volatility than positive shocks of similar scale.

Kumar and Khanna (2018) studied the volatility pattern and spillover of stock markets of four countries namely, India, China, Hong Kong, and Japan. The volatility behavior and the spillover was studied using ARCH, GARCH (1,1), and bivariate GARCH - BEKK models. The results revealed the Chinese markets to be the most volatile market and Indian market to be comparatively stable markets compared to the other markets. The volatility persistence was also found to be highest in the Chinese market. The cross market ARCH effect was strongest between China and Japan followed by Hong Kong and Japan; it was weakest for China and India. Persistency of cross market volatility was highest for the pair of China and India followed by Hong Kong and India, and lowest for China and Japan.

Mukherjee and Goswami (2017) studied the volatility returns from commodity futures in India. Commodity futures of gold, crude oil, mentha oil, and potato were analyzed during the period from 2004 - 12. The rolling standard deviation revealed a decreasing volatility trend for potatoes and increasing volatility trend for gold. The results of GARCH (1,1) revealed a persistent volatility for all commodities except potato.

Maqsood, Safar, Shafi, and Lelit (2017) modeled the stock market volatility using GARCH models for Nairobi Securities Exchange during the period from March 2013 to February 2016. The study revealed a high degree of volatility persistence and evidence of risk premium in returns of NSE. The presence of leverage effect was confirmed by using asymmetric models of GARCH. The study revealed that asymmetric models better described the volatility of NSE.

Sahai (2016) studied the volatility modeling for the forecasting efficiency of GARCH models for soy futures in India and the USA. The results revealed a high degree of volatility persistence in soy oil futures, and the volatility effect decayed over time. The study concluded that GARCH (1,1) better modelled the volatility of soy oil futures. It was revealed that for soy oil futures in U.S., EGARCH (1,1) modelled volatility better.

Siddiqui and Siddiqui (2015) forecasted the volatility of commodity market using selected GARCH model. The results of GARCH model indicated that metal spot, energy spot, and metal futures exhibited a high degree of volatility persistence, but less in agriculture spot and energy futures. The results of EGARCH model indicated the presence of leverage effect. The results of CGARCH model indicated subsistence of trend and transitory component of volatilities in all indices except energy futures.

Banumathy and Azhagaiah (2014) studied the volatility of Indian stock markets using symmetric and asymmetric models of GARCH models. The study revealed that there is an existence of positive and insignificant risk premium which is reflected in the GARCH-M models. The leverage effect in the stock market was confirmed by using asymmetric models of GARCH models.

Singh and Ahmad (2011) compared the different GARCH models to model and forecast the conditional variance of S&P Nifty index. Various time series models have been tested for robustness using Gaussian, student *t* - test, and generalized error distribution. The study found out the TGARCH and PGARCH specifications to be ideal as it more consistently described the Nifty index volatility pattern.

From the review of literature, it can be seen most of the volatility modeling has been done in stock markets. Not many studies have been done on the commodity markets in India. Hence, the present study has been taken up.

Objectives of the Study

The primary objective of the study is to fit appropriate GARCH models to estimate the volatility of commodity markets in India. The objectives of the study are :

- To study the volatility pattern of the commodity market by using various symmetric and asymmetric GARCH models.
- To analyze the presence of leverage effect in daily return series of Indian commodity markets using asymmetric models of GARCH.
- To find an appropriate model that better describes the volatility of the Indian commodity market.

Research Methodology

(1) Data Description : The study is based on secondary data taken from the website of MCX. The indices of MCX such as MCX AGRI, MCX ENERGY, MCX METAL, and MCX COMDEX have been used for the analysis. The daily closing prices of indices from April 1, 2013 to March 31, 2018 have been used for the study (MCX, 2017).

(2) Tools Used for the Study : Various econometric tools like ADF test, PP test, and KPSS test were used to analyze the unit root properties of the series. The ARCH effect in the indices was analyzed by using ARCH-LM test. The volatility of the commodity market was analyzed by using various ARCH family models. The analysis was done using EVIEWS 7 Econometric Package. The volatility was analyzed on the return series of the indices. *Sp* before doing the analysis, the return of the series is generated by using the following formula :

$$Return_t = \log \frac{P_t}{P_{t-1}} \quad (1)$$

where, $Return_t$ is the logarithmic daily return of indices for time t, P_t is the closing price of the indices in the time t, and P_{t-1} is the closing price in the time period t -1.

(3) Descriptive Statistics : The basic properties of the series are analyzed using descriptive statistics. The descriptive statistics show the mean, standard deviation, skewness, kurtosis, and Jarque Bera statistics of commodity indices.

(4) Tests for Stationarity : The stationarity properties of the commodity indices have been analyzed by using stationarity tests like Augmented Dickey Fuller test, Philips - Perron test, and KPSS test. The stationarity of the series confirms that mean, variance, and autocorrelation remains constant over time.

(5) Tests of Heteroskedasticity : Before applying any GARCH model, it is necessary to confirm the presence of volatility clustering or ARCH effect. The presence of ARCH effect confirms that periods of high volatility are followed by periods of high volatility, and periods of low volatility are followed by periods of low volatility. Only after confirming the ARCH effect, we can proceed to apply the GARCH models in the data.

(6) Volatility Measurement of Commodity Indices : Various GARCH family models are applied to analyze the volatility of commodity markets. The symmetric and asymmetric models of GARCH models are applied to model the conditional volatility of commodity markets.

(7) Symmetric Volatility Models : As stated by Black (1976), the returns are negatively correlated with volatility. The symmetric GARCH models assume that conditional variance depends only on the magnitude and not on the negativity and positivity of the underlying asset. Basically, it assumes that both good news and bad news have same effect on volatility. Most popular symmetric GARCH models are GARCH (1, 1) model and GARCH-M (1, 1) model. These are applied in this study to model the symmetric effect of volatility in the commodity market.

(8) GARCH (1, 1) Model : The GARCH model developed by Bollerslev (1986) allows conditional variance to be dependent on its own lags. The specification for GARCH (1, 1) model can be written as follows :

Mean equation $r_t = \mu + \varepsilon_t$ (2)

Variance Equation $\sigma_t^2 = \omega + \alpha \varepsilon^2_{t-1} + \beta \sigma^2_{t-1}$ (3)

In equation (3), ε^2_{t-1} & σ^2_{t-1} represent the ARCH and GARCH terms, respectively. This shows the short run dynamics of volatility pattern of the series. In equation (3), if $\alpha + \beta < 1$, it shows low volatility ; $\alpha + \beta = 1$ shows high volatility ; and $\alpha + \beta > 1$ shows extreme volatility.

(9) GARCH - M Model : In this model, the dependent variable in the mean equation is determined by its conditional variance. Thus, expected return of the underlying asset is related to expected risk of the asset. Hence, the equation of GARCH-M model can be written as :

Mean equation $r_t = \mu + \lambda \sigma t^2_{\tau} + \varepsilon_t$ (4)

Variance Equation $\sigma_t^2 = \omega + \alpha \varepsilon^2_{t-1} + \beta \sigma^2_{t-1}$ (5)

The parameter λ in the mean equation is called risk premium. A positive value of λ indicates that the return of the asset is positively correlated with volatility. This implies that a rise in mean return is caused by an increase in conditional variance, which is used as a proxy of risk.

(10) Asymmetric Volatility Models : It is often found that bad news is more volatile than good news. In such a situation, symmetric models are unable to recognize it as they assume both good and bad news have the same effect on volatility. This implies that conditional variance answers asymmetrically to negative and positive residuals. Hence, a number of asymmetric models have been developed like EGARCH (1, 1) model by Nelson (1991) and TARCH (1, 1) model by Zakoian (1994).

(11) EGARCH (1, 1) Model : This model represents the log of conditional variance. The presence of leverage effect can be analyzed through this model which will help to capture the asymmetric effects in Indian commodities market. The following is the conditional variance equation of EGARCH (1,1) model :

$$\ln(\sigma^2_t) = \omega + \beta_1 \ln(\sigma^2_{t-1}) + \alpha_1 \left\{ \left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| - \sqrt{\frac{\pi}{2}} \right\} - \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \quad (6)$$

The left hand side represents the log of conditional variance. The coefficient γ represents asymmetry or leverage term. The presence of leverage effect can be confirmed if the term is negative and significant.

(12) TARCH (1, 1) Model : The TARCH model or threshold ARCH model was developed by Zakoian (1994). The generalized specification of TARCH model can be written as follows :

$$\sigma^2_t = \omega + \alpha_1 \varepsilon^2_{t-1} + \gamma d_{t-1} \varepsilon^2_{t-1} + \beta_1 \sigma^2_{t-1} \quad (7)$$

The term represented by γ denotes the leverage term. If the term is significant and positive, it is concluded that the bad news has more impact than good news.

Analysis and Results

The descriptive statistics are summarized in the Table 1.

Table 1. Descriptive Statistics of Commodity Indices

	MCX AGRI	MCX METAL	MCX ENERGY	MCX COMDEX
Mean	0.018	0.004	-0.019	-0.002
Median	0.015	-0.010	-0.017	-0.020
Maximum	3.632	5.705	6.902	5.438
Minimum	-3.561	-6.622	-6.223	-4.982
Std. Dev	0.790	0.912	1.746	0.867
Skewness	0.209	0.062	0.174	0.201
Kurtosis	5.153	9.617	4.576	6.860
Jarque Bera	247.512	2252.354	133.992	774.482
Observations	1234	1234	1234	1234

From the Table 1, it can be seen that there is a positive return for MCX AGRI and MCX Metal and there is a negative return for MCX Energy and MCX COMDEX. The analysis of skewness reveals that the returns of all the indices are positively skewed. Hence, there is high probablity that the returns are less than the mean return. The value of kurtosis is found to be higher than 3, indicating that the series is platykurtic, which if further confirmed by the significant Jarque - Bera statistics, which indicates that the series is not normal.

Before doing the volatility model, the series needs to be converted into stationary. For making the series stationary, the series are converted to their return series. The return series are plotted in a graph to understand the volatility clustering. The graph is plotted in Figure 1. From the graph, it can be seen that low periods of volatility are followed by low periods of volatility and high periods of volatility are followed by high periods of volatility. This shows that the series of commodity indices exhibit periods of volatility clustering, and the mean and variance of the return series are constant over a period of time.

The unit root tests have been performed to analyze the stationarity properties of the series. The Augmented Dickey Fuller test and Philips - Perron test have been used to perform the unit root analysis. The test for

Figure 1. Volatility Clustering of Daily Returns of MCX Commodity Indices

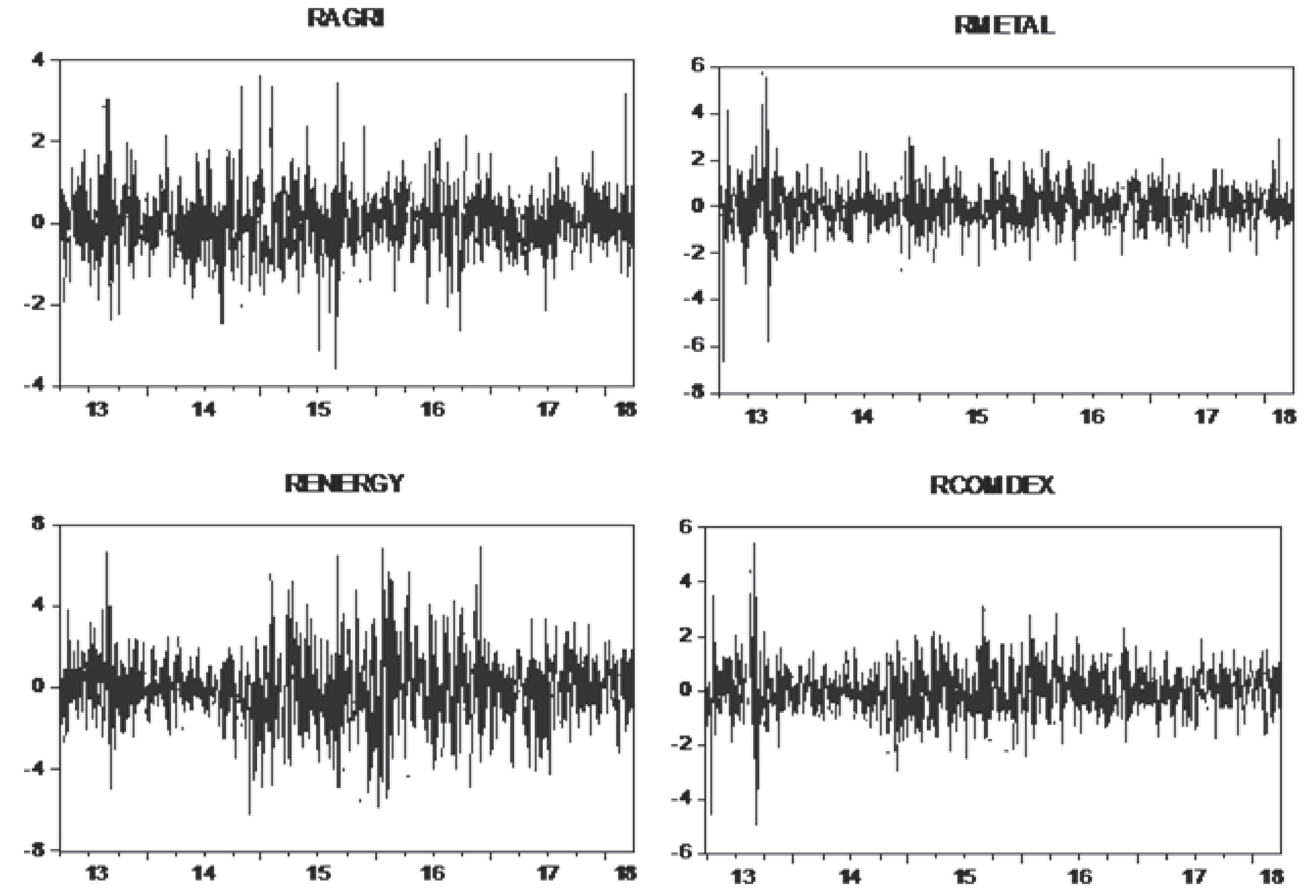

Table 2. Results of Unit Root Tests and Results of ARCH - LM Tests for Heteroskedasticity

Value	MCX AGRI		MCX METAL		MCX ENERGY		MCX COMDEX	
	ADF	PP	ADF	PP	ADF	PP	ADF	PP
t - statistics	-21.809	-34.363	-37.032	-37.086	-34.287	-34.337	-35.092	-35.158
p - value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
ARCH LM Test for Residuals								
ARCH LM Statistic	17.913		12.047		80.947		13.811	
p - value	0.000		0.000		0.000		0.000	

heteroskedasticity, ARCH-LM test was conducted on the series, and the results are presented in the Table 2. From the table, it can be seen that the *p* - values of all the variables are less than 0.05, which confirms that the series are stationary. The results of ARCH- LM test show significant chi - square values, which show the presence of ARCH effect in all the series. Thus, the volatility clustering in the return series is confirmed in return series of all indices of MCX.

After confirming volatility clustering on the return series, stationarity tests using ADF and PP tests and heteroskedasticity using ARCH LM tests, we can proceed to determine the best fitted model to model the volatility in commodity markets. The results of GARCH (1, 1) model are presented in the Table 3.

From the Table 3, it can be seen that the coefficients, ω, α, and β are statistically significant. The values of

Table 3. Results of GARCH (1, 1) Model

Coefficients	MCX AGRI	MCX METAL	MCX ENERGY	MCX COMDEX
		Mean Equation		
μ(Constant)	0.028	0.004	-0.003	0.011
		Variance Equation		
ω (Constant)	0.021*	0.014*	0.032*	0.032*
α (Arch Effect)	0.050*	0.039*	0.076*	0.087*
β (GARCH Effect)	0.917*	0.940*	0.916*	0.867*
α + β	0.967	0.979	0.992	0.954
Log Likelihood	-1427.824	-1548.017	-2334.420	-1498.165
AIC	2.320	2.515	3.789	2.434
SIC	2.337	2.532	3.806	2.451
		ARCH LM Test for Heteroskedasticity		
ARCH LM Test Statistic	0.713	0.256	0.293	0.012
Prob. Chi Square	0.398	0.612	0.588	0.912

Note. * significance at the 1% level.

Table 4. Results of GARCH in Mean (1, 1) Model

Coefficients	MCX AGRI	MCX METAL	MCX ENERGY	MCX COMDEX
		Mean Equation		
μ (Constant)	0.105	0.072	-0.106	0.135
λ (Risk Premium)	-0.101	-0.083	0.072	-0.157
		Variance Equation		
ω (Constant)	0.020*	0.014*	0.031*	0.035*
α(Arch Effect)	0.049*	0.039*	0.076*	0.092*
β (GARCH Effect)	0.920*	0.941*	0.916*	0.859*
α + β	0.969	0.980	0.992	0.951
Log Likelihood	-1427.689	-1547.873	-2334.116	-1497.603
AIC	2.322	2.517	3.791	2.435
SIC	2.343	2.538	3.812	2.456
		ARCH LM Test for Heteroskedasticity		
ARCH LM Test Statistic	0.851	0.188	0.214	0.0002
Prob. Chi Square	0.356	0.664	0.643	0.988

Note. * significance at the 1% level.

coefficient β are significantly higher than α, indicating a longer memory and volatility of the indices are sensitive to their own lagged values than new information in the market. The size of α + β indicates the volatility persistence of the commodity indices. The value of all indices is very close to 1, indicating a high level of volatility persistence. This confirms that the volatility takes a longer time to reduce. The diagnostic checking of the presence of ARCH effect has been done using ARCH LM test. The p value of the test is found to be higher than 0.05, indicating the absence of ARCH effect in residuals of the model. This confirms that the model is well specified. The results of GARCH-M (1, 1) model have been presented in the Table 4.

The GARCH-M model allows the return in mean equation to be dependent on the conditional variance. From

Table 5. Results of EGARCH (1, 1) Model

Coefficients	MCX AGRI	MCX METAL	MCX ENERGY	MCX COMDEX
		Mean Equation		
μ(Constant)	0.026	0.015	-0.016	0.023
		Variance Equation		
ω (Constant)	-0.167*	-0.076*	-0.099*	-0.155*
α (Arch Effect)	0.177*	0.094*	0.145*	0.182*
λ (Leverage Effect)	-0.011	0.016*	-0.036*	0.0004*
β (GARCH Effect)	0.938*	0.987*	0.988*	0.963*
α + β	1.115	1.081	1.133	1.145
Log Likelihood	-1424.707	-1552.641	-2330.193	-1503.476
AIC	2.317	2.525	3.785	2.445
SIC	2.337	2.545	3.805	2.466
		ARCH LM Test for Heteroskedasticity		
ARCH LM Test Statistic	0.353	0.836	0.759	0.086
Prob. Chi Square	0.552	0.360	0.383	0.769

Note. * significance at the 1% level.

Table 6. Results of TGARCH (1, 1) Model

Coefficients	MCX AGRI	MCX METAL	MCX ENERGY	MCX COMDEX
		Mean Equation		
μ (Constant)	0.027	0.013	-0.017	0.013
		Variance Equation		
ω (Constant)	0.016*	0.016*	0.029	0.032*
λ (Arch Effect)	0.034*	0.052*	0.050	0.090*
β (Leverage Effect)	0.022	-0.028*	0.049*	-0.005
β (GARCH Effect)	0.930*	0.939*	0.918	0.869*
α + β	0.964	0.991	0.968	0.959
Log Likelihood	-1426.557	-1545.655	-2331.048	-1498.139
AIC	2.320	2.513	3.786	2.436
SIC	2.341	2.534	3.807	2.456
		ARCH LM Test for Heteroskedasticity		
ARCH LM Test Statistic	1.089	0.622	0.267	0.027
Prob. Chi Square	0.296	0.430	0.605	0.869

Note. * significance at 1% level.

the Table 4, the coefficient λ is insignificant in all the series. This confirms that there is no significant impact of volatility on the return of the indices under study. In the conditional variance equation, it can be seen that the ARCH term α and the GARCH term β are significant in all cases. The sum of α + β is also found to be close to unity, indicating a high level of volatility persistence. The residual test of ARCH LM test shows the absence of ARCH effect, indicating that the model is well specified. The asymmetric models of GARCH help to capture the leverage effect, if any in the time series. The EGARCH (1, 1) model results are presented in the Table 5.

From the Table 5, it can be seen that the presence of leverage effect is confirmed only in the case of MCX

ENERGY and not in any other indices. The volatility persistence is found to be extremely high in all the indices as the total of $\alpha + \beta$ is found to be greater than unity. So, it can be concluded that there is a negative correlation between past returns and future returns only in case of MCX ENERGY. The good news and bad news have equal impact on all other indices as there is absence of leverage effect in those series. Finally, the diagnostic checking of no ARCH effect is confirmed with the insignificant values of test statistic of ARCH - LM test. Another asymmetric model for modeling the volatility is TGARCH model, which has been developed by Zakoian (1994). The results of TGARCH (1, 1) model have been presented in the Table 6.

The Table 6 shows the TARCH (1,1) model of commodity indices. The analysis shows that the coefficient of leverage effect, λ is positive and significant only in MCX ENERGY. This confirms the presence of asymmetric effect in MCX ENERGY index. The diagnostic checking of no ARCH effect is confirmed by insignificant *p* - values.

Findings of the Study

The analysis reveals that the volatility persistence is very high in commodity market as the value of $\alpha + \beta$ is very high in all the models. The volatility persistence is found to be explosive in EGARCH (1, 1) model. The asymmetric effects of the indices are captured using EGARCH (1, 1) and TARCH (1, 1) models. The analysis reveals that MCX ENEGRY index shows leverage effect, where bad news creates more volatility than good news.

For MCX AGRI, the lowest AIC and SIC are found in the EGARCH (1, 1) model. So EGARCH (1, 1) model is found to be the best fitted model that describes the volatility pattern of MCX AGRI. For MCX METAL, the lowest AIC and SIC are found in the TARCH (1, 1) model. So, TARCH (1, 1) is found to be the best fitted model that describes the volatility pattern of MCX Metal. For MCX ENERGY, the lowest AIC and SIC are found in the EGARCH (1, 1) model. So EGARCH (1, 1) model is found to be best fitted model that describes the volatility pattern of MCX Energy. For MCX Comdex, the GARCH (1, 1) model is found to have the lowest AIC and SIC ; hence, it is the best fitted model. Our results are in line with the study results of Siddiqui and Siddiqui (2015).

Conclusion

In this study, volatility of commodity indices are analyzed using various GARCH family models. The daily closing prices of four indices of MCX such as MCX AGRI, MCX METAL, MCX ENERGY, and MCX COMDEX were analyzed by using various symmetric and asymmetric GARCH family models for the period of April 1, 2013 to March 31, 2018. The symmetric volatility models such as GARCH (1, 1) and GARCH M (1, 1) have been employed, which reveals that there is a high degree of volatility persistence in the commodity market. The risk premium is found to have no impact on the returns of commodity indices. The asymmetric volatility models like EGARCH (1, 1) model and TARCH (1, 1) model have been applied to analyze the leverage effect in the commodity market. The analysis reveals that there is presence of leverage effect only in the case of MCX ENERGY. All other indices are found not to exhibit the leverage effect. Finally, AIC and SIC criteria are used to identify the best model which describes the volatility of the commodity market. It is found that EGARCH (1, 1) model best fits among all other models for MCX AGRI and MCX ENERGY. For MCX Metal, TARCH (1, 1), model is found to be the best fit. For MCX COMDEX, GARCH (1, 1) model best describes the volatility.

Research Implications

The study attempts to do a volatility modeling of the Indian commodity market using the GARCH family models. The findings of the research will be helpful for risk management, derivative pricing and hedging, market timing, portfolio selection, and many other financial activities. As new approaches are identified and tested, a financial manager should be able to take critical decisions regarding the selling of stocks or commodities before these become too volatile or increasing a bid-ask spread when the future is expected to be volatile.

Limitations of the Study and Scope for Further Research

The study uses data for the period from January 1, 2013 to March 31, 2018. More inferences could be made if the data period was longer. The study has not used intraday data, which might give more insights about volatility in the commodity market.

Studies can be conducted on individual commodities to get a clearer picture of commodity wise volatility. The study can be extended further by using other models such as APARCH model, PARCH model, etc.

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