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EXPLORING ASYMMETRIC GARCH MODELS FOR PREDICTING INDIAN BASE METAL PRICE VOLATILITY

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Abstract

Research background: Many studies have been done in the field of predicting the Volatility of Commodities; however, very little or no analysis has been conducted on any sector, industry, or indices to identify which model is best to understand the asset's characteristics, as there is a hypothesis that all financial time series can be interpreted by implementing the same model.

Purpose: The primary objective is to identify different tools developed by the researchers in estimating impulsive clustering and leverage effects. A comparison will be made among the available tools of the GARCH family models to suggest the best tool to forecast and calculate volatility with the least error.
Research methodology: The data used are historical time series data of Indian base metal indices, i.e., Aluminum (AL), Copper (CO), Lead (LE), Nickel (NI), and Zinc (ZI) from NSE for a period from 1st June 2012 to 31st August 2022 from the official website of NSE of India. The study compared and attempted to identify which GARCH family model is suitable to measure the volatility clustering and leverage effect in Indian base metal indices by reducing the chances of error.
Results: The study has revealed that the GRACH asymmetric models, while approximating and predicting the financial time series, can enhance the model's output when it has a high frequency. Here, the asymmetric GARCH models (TARCH, CGARCH, EGARCH, and PARCH) better predict volatility than classic models.
Novelty: This study is original in its approach, as a previous study stated the presence of volatility or leverage effect by implementing any one tool. However, this study will compare available tools to suggest which is appropriate for which sector. This analysis will support future researchers and practitioners in evaluating volatility clustering and the effect of leverage by implementing the appropriate GARCH family model without believing in a hypothesis that a single model is good enough to predict volatility.

Keywords: Volatility, asymmetric GARCH, Base Metal, forecasting, Sustainability

JEL classification: C01, C10, C 12, E41, E44

Introduction

Predicting and modeling volatility is considered to be one of the crucial ingredients in the financial markets. Several research studies have already been conducted on developing various models to resolve the issues, as this prediction leads to efficient risk management and price of the financial assets. In the last three decades, a wide study has been conducted on financial market volatility empirically like:

Mandelbrot (1963) stated that in the financial time series, the basic outcome that can be felt is the presence of impulsive clustering and leptokurtosis. It is more confirmed that the time series' financial returns are non-normally distributed, leading to fat-tailed. Moreover, Mandelbrot (1963) strongly refused the existence of a normal distribution of the data set.

Leveraging Financial and operating on fixed costs provides a partial output of the fluctuation, which Black (1976) solved for the first time, revealing the response of change in volatility towards good news and bad news.

Harris and Sollis (2003) proposed that in a financial time series, expecting a long memory is a regular phenomenon like other time series (e.g., macroeconomics), but the property of the existence of long memory can be interpreted through the high frequency in the financial time series. These states about the presence of information impact on the financial time series make long-range dependency and affect the future counts.

Another vital element is the volatility with the time variance, otherwise called heteroscedasticity of data in the financial time series. It means the variance or change in volatility (Kumar, 2019; Kumar *et al.*, 2019a).

This kind of variance needs special treatment as it cannot be understood through linear models, i.e., RW and OLS. These variances can be interpreted effectively by Bollerslev (1986) and Engle (1982) through the Generalised Auto-Regressive Conditional Heteroscedasticity (GARCH) and Auto-Regressive Conditional Heteroscedasticity (ARCH) models, respectively. ARCH models were widely used in analyzing financial markets. This is mostly used for high-frequency data and a heavy peaked and tailed distribution.

Apart from all this, EMH (Efficient Market Hypothesis) is an analysis that an investor may choose to analyze through past prices. However, there is a consideration that the market is only moderately competent. For instance, if the market is strongly efficient, then the performance of the assets can be forecasted from their past prices or behavior. (Miron, Tudor, 2010; Peters, 2001; Sahoo *et al.*, 2024).

Volatility in financial assets can be taken for granted as an element of the rise in risk, which may produce a financial crisis (Kumar, 2018a). So, volatility should be given priority in making any investment decisions. Investors believe volatility helps calculate derivatives for discovering the spot price of assets and certain critical decisions for portfolio designing and hedging strategies (Kumar, 2018b). Policymakers keep an eye on volatility and take major steps to maintain a balanced performance in the financial markets.

This study aims to identify the superior volatility model for Indian base metal indices by asymmetric GARCH models. This study will be a novel approach as the previous researcher measured the presence of impulsive clustering or leverage effect by implementing a particular model. As per the knowledge, very little or no analysis is conducted on any sector, industry, or indices to identify which model is best to understand the asset's characteristics, as there is a hypothesis that all financial time series can be interpreted by implementing the same model.

The paper is represented with different sections. Section 1 states the conceptual study on GARCH family models and previous studies. In Section 2, the Research methodology highlights the data setting and all the tools used in the study. In section 3, an analysis is conducted on the GARCH family models to identify the superiority of Indian base metal volatility. Section 4 states the results of the analysis and Section 5 discusses the conclusions, implications of the study.

1. Literature review

The stock return highlight on volatility clustering, Leverage effect, and Leptokurtosis was proposed by three learned researchers: Black, F (1976), Fama E.F. (1965), and Benoit M. (1963). Several researchers commented that traditional time series models are based on an assumption of constant variance that does not provide true estimated results on the movement of stock return. Hence, a new model is presented, i.e., suggested the ARCH models by Engle (1982) that avoid the past issues parting the unconditional variance constant by changing conditional variance over time. The limitation of the ARCH model assumption, i.e., specifying the conditional variance as a linear function, was solved by subsequent researchers. Bollerslev (1986) suggests the GARCH Model (Generalized ARCH), which considers the features of ARCH and lagged conditional variances. The GARCH model also supports longer data with flexible lag selection. Engle *et al.* (1987) proposed an advanced method of the ARCH model, where it considers the mean to determine the conditional variance and named it GARCH-M. This empirical study supports the identification that risk premiums are not time-invariant but rather systematic. With the lapse of time, it was further observed that the GARCH model has several limitations, which were identified and solved by Nelson (1991), exploring the positive or negative return and inconsistency through a model. The proposed model is named the EGARCH (Exponential GARCH) model.

GJR GARCH, a model introduced by Glosten *et al.* (1993), is an advanced model to GARCH-M, which shows uneven volatility due to the shock of positive and negative returns. With time, several studies were made, and improved models were supplemented with GARCH models to solve the drawbacks of each model. Ding *et al.* (1993) proposed APGARCH (Asymmetric Power GARCH), Zokoian (1994) gave TGARCH (Threshold GARCH), and many more. Many researchers like (Hsieh, 1989; Taylor, 1994; Bekaert, Harvey, 1997; Aggarwal *et al.*, 1988; Brook, Burke, 2003; Frimpong, Oteng, 2006; Olowe, 2009) concluded about the ARCH and GARCH models that volatility measurement can only be possible GARCH (1, 1). A comparing review of GARCH-M, EGARCH, TGARCH, and PGARCH is stated by a few researchers based on researchers such as (Su, 2010; Miron, Tudor, 2010; Awartani, Corradi, 2005; Gokan, 2000) that all the asymmetric models in GARCH helps to predict the volatility of daily return on stock throughout the world. Amongst all of the EGARCH models, it fits best to measure the volatility.

Kumar *et al.* (2019b) conducted a study on the NSE and Spot Index future by implementing GARCH family models. The study has used Nifty 50 futures and spots along with their indices, i.e., bank index, inflation index, and IT index, from Jan 1st, 2007, to Jun 30th, 2018. The study reveals that volatility clustering can be predicted from the GARCH models along with the stock market characteristics, while the effect of leverage can be measured through EGARCH. A few analyses are also made on emerging stock markets for volatility estimation and prediction by considering ARCH and GARCH models. The researchers being Akgül and Sayyan (2005) and, Kumar and Mishra (2019a) of India, Rashid and Ahmad (2008) in Pakistan, R. Gokbulut and M. Pekkaya (2014) in Turkey. Their analysis concludes that the data from emerging economies shows Leptokurtosis, non-normality, negative skewness, volatility clusters, and GARCH (1, 1) as the best fit. Meanwhile, CGARCH and TGARCH are supported by Gokbulut and Pekkaya (2014) as they find them more suitable for measuring volatility. A series of analyses were conducted by researchers from emerging countries like Kumar and Mishra (2019b), Floros (2008) in Nigeria, Moustafa Abd *et al*. (2011), Angabini and Wasiuzzaman (2011) in Malaysia, Ezzat Hassan (2012) of Egypt, Su (2010) in China, Emenike (2010) and Freddie *et al.* (2012) of Saudi Arabia who made a comparison of various models from the GARCH and ARCH family and concluded that GARCH, GJR GARCH, and EGARCH are fitting for the clustering effect, leptokurtosis volatility measurements, and identifying leverage effect. Kumar and Biswal (2019) attempted a study to measure the volatility clustering and leverage effect of top future stock markets from Jan 1st, 2014, to Oct 31st, 2018, by implementing the GARCH family model. The study confirms that EGACRH can be accepted for analyzing the leverage effect while estimating the characteristics of the stock market. GARCH (1, 1) is the best model.

1.1. Problem of the study

The Commodity market is always volatile, and as a result, the practitioner is unable to identify the performance and forecast accurately. This confusion put the practitioners at a great loss. As a result, several research studies were conducted to measure the volatility and the leverage effects. It is difficult to estimate the volatility accurately by implementing the right technique. So the main issue is, can we suggest the best technique out of the list of tools for certain Commodity markets?

1.2. Purpose of the study

As per the problem of the study, the primary objective is to identify different tools developed by the researchers in estimating impulsive clustering and leverage effects. A comparison will be made among the available tools of the GARCH family models to suggest the best tool to forecast and calculate volatility with the least error. This study is original in its approach, as the earlier study stated the presence of volatility or leverage effect by implementing any one tool. However, this study will compare the available tools to suggest which is appropriate for which sector.

2. Research methodology

2.1. Collection of data

The historical time series data of Indian base metal indices, i.e., Aluminum (AL), Copper (CO), Lead (LE), Nickel (NI), and Zinc (ZI) from MCX for a period from 1st June 2012 to 31st August 2022 from the official website of MCX of India were undertaken for the research.

2.2. Statistical tools

The tools used are as follows:

a) ***Calculation of indices daily average:*** The data available, i.e., open prices, high prices, low prices, and close prices for all the periods are taken. The average of these four prices is considered for analysis, i.e.

Average prices of Indices (Daily) = (open + high + low + close)/4.

Most of the researchers have considered the closing price. However, it will not be rational to consider the closing price only as in a day; the index may open at a high price and continue high for the whole day and then at a minimum while closing or vice versa.

b) ***Adjusted return Calculation:*** The calculation of the adjusted return is as follows:

$$R_{it} = LN \, {}^{P_{it}}\!\big/_{P_{it-1}}$$

where, P_{it} and P_{it-1} state the natural logarithm of the Commodity's average price of day t and the previous day t, respectively. The natural logarithm average returns are used to present nonstationary and avoid future price variability.

Descriptive Statistics: A return series of Indian Base metal is accepted to detect distributional practices through descriptive statistics. The outcome displays Jarque-Bera Statistics, Standard Deviation (σ), Kurtosis (K), Mean(X), and Skewness (S).

c) ***Test of Normality***

Jarque-Bera (JB) Statistics: A Lagrange multiplier test used for normality assessment. For several statistics to measure the normality, the Jarque-Bera test is applied. The JB test is run before one of these tests to confirm the presence of these tests. When the data series is large, other kinds of tests are unreliable; hence, the JB test is run.

$$JB = \frac{N}{6}S + \frac{N}{24}K$$

$$JB = \frac{N-k}{6}\left[s^2 + \frac{1}{4}(K-3)^2\right]$$

where, k explains the estimated number of coefficients, K is the Kurtosis, and S is the Skewness.

d) ***Data Stationary:*** The most important test for a time series is the test of the unit root. The unit root test states the stationary and non-stationary data. The unit root test is calculated as per the (Dickey, Fuller, 1979) by implementing the Augmented Dickey-Fuller test (ADF) and the Phillips-Perron (1988) Test (PP-Test)

It depends on the following model, where p is the lag.

$$\Delta Y_t = \alpha + \beta_t + \gamma Y_{t-1} + \partial_1 \Delta Y_{t-1} + \ldots + \partial_{p-1} \Delta Y_{t-p+1} + \varepsilon_t$$

where α – constant, β – time trend coefficient and p value is the lag order of the autoregressive process, ε_t – white noise error term.

The regression with the AR (1) process, the mathematical formula for the Phillips-Perron (PP) test is shown as.

$$\Delta Y_{t-1} = \alpha_0 + \gamma \mathrm{Y}_{\mathrm{t-1}} + \varepsilon_t$$

e) ***AIC and SBC has been used for choosing the Best ARMA (p, q) model***

AIC and SBC are considered to determine the ARMA (p, q) model. ARMA (p, q) is simulated first to show this method. The values are paired and looped pϵ {0, 1, 2, 3, 4, 5, 6} and q ϵ {0, 1, 2, 3, 4, 5, 6} and evaluate the AIC and SBC. The model will then be selected based on the lowest value of AIC and SBC.

Akaike Information Criterion: AIC = –2log (L) + 2K

SBC-Schwarz Criterion SBC = –2log (L) + K log (n)

f) ***Autoregressive Conditional Heteroskedasticity (ARCH)***

The serial correlation of Heteroskedasticity, i.e., the relation within the heteroskedasticity, is called the ARCH effect. It often gets outward when there lies a clustering of fluctuation or movements of a particular element by making a certain form, which some factors can explain.

The model is as follows:

$$Y_t = \beta_o + \beta_1 X_t + u_t$$

$$u_t = N\left(0, \alpha_0 + \alpha_1 u_{t-1}^2\right)$$

Depending on the squared error term lagged one time period; this signifies that the error term is normally distributed with the mean as zero and conditional variance.

When the error terms are presented with a lagged one or two, it is the conditional variance:

$$\sigma_t^2 = var\left(ut \setminus u_{t-1}, u_{t-2} \ldots\right) = E\left(u_t^2 \setminus u_{t-1}, u_{t-2}\right)$$

where the error term, of the conditional variance is presented as σ_t^2. Then the model for presenting the ARCH effect is:

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2$$

g) ***Generalised Autoregressive Conditional Heteroskedasticity (GARCH)***

The GARCH model came into existence in 1986 by Bollerslev, including lagged square residuals and standard deviation. The model can be presented as:

$$\sigma_t^2 = \alpha_0 + \sum \alpha_1 u_{t-1}^2 + \sum \beta_1 \sigma_{t-1}^2$$

where σ_t^2 is conditional volatility, u_{t-1} is defined as an error or residual and σ_{t-1}^2 is the lagged conditional volatility which make the GARCH different from the ARCH. In which $\beta_1 \sigma_{t-1}^2$ is the GARCH element.

h) ***Exponential Generalised Autoregressive Conditional Heteroskedasticity (EGARCH)***

The further development termed the asymmetric GARCH model was developed by Nelson (1991), who defined it as EGARCH. The additional component introduced was the Exponential component in ARCH. The objective is to reduce the basic standard GARCH from the positive constraints. However, it also contains non-negatives for the conditional variance on the volatility.

$$\text{In}\left(\sigma_t^2\right) = \alpha_t + \sum_{t=1}^{\infty} \beta g\left(z_{t-i}\right)$$

where the function $g(z_t)$ can be represented in different ways. Nelson (1991) suggested using mod z_t to control both signs, i.e., positive and negative, without affecting the magnitude of z_t

i) ***Threshold Generalised Autoregressive Conditional Heteroskedasticity (TGARCH)***

The form of the GARCH family is the threshold GARCH model that is capable of modelling the leverage effects. It can be presented as:

$$\sigma_t^2 = \alpha_0 + \sum_{t=1}^{p} \alpha_t u_{t-1}^2 + \sum_{t=1}^{p} \alpha_t S_{t-1} u_{t-1}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2$$

where:

$$S_{t-1} = \begin{cases} 1 \text{ for } u_{t-1} < 0 \\ 0 \text{ for } u_{t-1} \geq 0 \end{cases}$$

j) ***Power Generalised Autoregressive Conditional Heteroskedasticity (PGARCH)***

Ding (1993) presented a special case by introducing power to the basic GARCH component to identify the leverage effect and named it as PGARCH.

$$\sigma_t^d = \alpha_0 + \sum_{t=1}^{p} \alpha_t \left(u_{t-i} + {}^\wedge yiu_{t-i} \right)^d + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^d$$

where $d > 0$, and y_i represents the leverage effect coefficient. When $d = 2$, it can be confirmed that it reduces the leverage effects of the basic GARCH model.

k) ***Component Generalised Autoregressive Conditional Heteroskedasticity (CGARCH)***

This model came into existence in 1993 by Engle and Lee. This model sets components as temporary and permanent by decomposing the variance. This can be represented as:

$$\sigma_t^2 = q_t + \alpha\left(\varepsilon_{t-1}^2 - q_{t-1}\right) + \beta\left(\sigma_t^2 - q_{t-1}\right)$$

$$q_t = \alpha_0 + p\left(q_{t-1} - \alpha_0\right) + \varnothing\left(u_{t-1}^2 - \sigma_{t-1}^2\right)$$

whereas, q_t represents a permanent component, p represents the long memory, α and β represent the short-term.

Mathematically, the asymmetric CGARCH can be presented as:

$$\sigma_t^2 = q_t + \alpha\left(\varepsilon_{t-1}^2 - q_{t-1}\right) + \gamma\left(\varepsilon_{t-1}^2 - q_{t-1}\right) + \beta\left(\sigma_t^2 - q_{t-1}\right)$$

$$q_1 = \alpha_0 + p\left(q_{t-1} - \alpha_0\right) + \varnothing\left(u_{t-1}^2 - \sigma_{t-1}^2\right)$$

3. Results

As per the study's objective time to suggest the appropriate model for estimating and predicting commodity market volatility, the primary research is to understand whether the selected sectors follow a normal distribution. The study implemented the Jarque Bera test on all of the selected sectors to conduct the normality test. Table 1 highlights the outcome of descriptive statistics and the test of normality of the data with the Jarque-Berra Test.

Table 1. Test of normality of the Indian Base metal Indices

	AL	CO	LE	NI	ZI
Mean	0.001434	0.001280	0.001257	0.000911	0.001309
Median	0.004691	0.004040	0.005315	0.004174	0.002496
Maximum	2.193505	2.110780	1.994326	2.077379	2.048816
Observations	3,066	3,066	3,066	3,066	3,066
Minimum	–2.426508	–2.027972	–1.989997	–2.044818	–2.039237
Std. Dev.	0.624521	0.653441	0.629382	0.653928	0.648477
Jarque-Bera	918.7122	881.2564	941.4358	833.2711	853.8376
Skewness	–0.152807	–0.106635	–0.168591	–0.107714	–0.133458
Kurtosis	5.664223	5.617786	5.693635	5.544850	5.571462
Probability	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	4.395603	3.925933	3.853613	2.793655	4.013656
Sum Sq. Dev.	1,195.432	1,308.710	1,214.114	1,310.660	1,288.902

Source: own elaboration.

Table 1 provides descriptive statistics and the results of the Jarque-Bera test for normality for the Indian Base Metal Indices, including Aluminum (AL), Copper (CO), Lead (LE), Nickel (NI), and Zinc (ZI). The mean, median, maximum, minimum, standard deviation, skewness, and kurtosis and the number of observations are reported for each index. The Jarque-Bera statistic is a test for normality, with a lower probability indicating a departure from normality. In this case, the probability values for all indices are zero, suggesting a statistically significant departure from normality. Skewness values are negative for all indices, indicating a negatively skewed distribution, while the kurtosis values are greater than three, indicating leptokurtic distributions with heavier tails than a normal distribution. These findings suggest that the return distributions for all indices exhibit a long left tail, indicating a higher probability of extreme negative returns.

The ADF test is considered a negative test. The more negative, the better and stronger the rejection of the hypothesis that, at some level of confidence, it lays a unit root.

It depends on the subsequent model, where p is the lag.

$$\Delta Y_t = \alpha + \beta_t + \gamma \mathrm{Y}_{\mathrm{t-1}} + \partial_1 \Delta \mathrm{Y}_{\mathrm{t-1}} \ldots + \partial_{\mathrm{p-1}} \Delta \mathrm{Y}_{\mathrm{t-p+1}} + \varepsilon_t$$

where ε_t = error term for white noise, p value is the autoregressive lag order, β = coefficient of time trend and α = constant.

Concerning error distribution in ADF, it gives a mild output, solved after the PP-Test presented by Phillips and Perron (1988) and Asteriou and Hall (2011). The regression with the AR (1) process, the mathematical formula for the Phillips-Perron (PP) test is shown as.

$$\Delta Y_{t-1} = \alpha_0 + \gamma \mathrm{Y}_{\mathrm{t-1}} + \varepsilon_t$$

Table 2. Data Stationary of Indian Base metal Indices

Indices	Intercept		Trend and intercept		None	
	t-statistic	prob.	t-statistic	prob.	t-statistic	prob.
Testing the presence of Unit root through the ADF Test						
Aluminum	–20.80592	0.0000	–20.83388	0.0000	–20.80373	0.0000
Copper	–22.82349	0.0000	–22.82551	0.0000	–22.82586	0.0000
Lead	–22.35278	0.0000	–22.35624	0.0000	–22.35270	0.0000
Nickel	–23.26018	0.0000	–23.26526	0.0000	–23.26018	0.0000
Zinc	–22.94033	0.0000	–22.93820	0.0000	–22.93763	0.0000
Testing the presence of Unit root through the PP test						
Aluminum	–524.3999	0.0001	–535.4517	0.0001	–508.2858	0.0001
Copper	–600.5614	0.0001	–600.3762	0.0001	–584.7426	0.0001
Lead	–571.5705	0.0001	–571.8146	0.0001	–569.9059	0.0001
Nickel	–624.9083	0.0001	–628.7631	0.0001	–609.9581	0.0001
Zinc	–703.9319	0.0001	–703.6525	0.0001	–687.1815	0.0001

Source: own elaboration.

Table 2 shows the output of the ADF and PP tests at the 1% level of significance; the result confirms that the data series in both tests are stationary as the probability statistics are less than zero along with that the results of absolute values are found to be larger than the critical values so the study rejects the hypothesis.

3.1. Identifying the mean equations

The data series of stationary and non-normality confirmation helps to proceed to the next step, identifying whether the return series depends on its past values. From Table 3, the result states that AR (2) and MA (1) are the best-fitting ARMA Models for all the data series.

Table 3. The ARMA model through minimum AIC and SBC for the metal index

Indices	Criteria	
	Akaike info. criterion	Schwarz criterion
Aluminum	1.162611	1.1684611
Copper	1.181319	1.1871750
Lead	1.156424	1.1622790
Nickel	1.210143	1.2159980
Zinc	1.200566	1.2064210

Source: own elaboration.

From Table 3, it is clear that AR2 and MA1 are considered to be the best ARMA models through the AIC and SBC selection criteria for all the data series, as this model shows the minimum value of AIC and SBC while others show the higher values and are found insignificant.

As per the research objective of approximating and predicting the best-fitting model for evaluating the volatility clustering of the Indian base metal indices, further analysis is carried out. For the analysis, the GARCH family models are used, i.e., ARCH (1), GARCH (1, 1), TARCH (1, 1), EGARCH (1, 1), PARCH (1, 1), CGARCH (1, 1). The accurate numbers of lags in the model are considered by selecting the lowest AIC and SBC information criteria. Table 4 is considered for identifying the best-predicting models for the Indian base metal indices.

Table 4. GARCH Models

GARCH FAMILY	A	B	C	D	E	F
1	2	3	4	5	6	7
GARCH Models of Aluminum through ARMA (2, 1)						
α_0(constant)	0.197311*	0.000148*	–7.10E–05	–0.040498*	0.328919*	0.258592*
(ARCH) A	–0.03099*	0.021536*	0.066685*	0.050243*	–0.05458*	–0.04209*
(Asymm-int) ὃ	–	–	–0.06193*	0.025999*	0.685619*	–
(GARCH) B	–	0.976831*	0.979688*	0.997720*	0.999982*	–0.821911*
Δ	–	–	–	–	0.068523*	–
P	–	–	–	–	–	–0.30937*
Φ	–	–	–	–	–	0.229552*

1	2	3	4	5	6	7
ARCH LM Test	0.675600	0.304700	0.195000	0.481400	0.021400	0.148700
AIC	1.183859	0.720898	0.706771	0.697500	0.899085	1.264744
SBC	1.193621	0.732612	0.720438	0.711167	0.914703	1.280362
F Statistics	0.175074	1.053089	1.679537	0.495524	5.300391	2.087092
GARCH Models of copper through ARMA (2,1)						
α_0(constant)	0.203771*	0.115283*	0.082446*	–0.82983*	0.359423*	0.306401*
(ARCH) A	–0.05344*	–0.05967*	0.153571*	–0.66405*	–0.09465*	–0.09288*
(Asymm-int) ϑ	–	–	–0.21657*	–1.07962*	0.648509*	–
β(GARCH)	–	0.461602*	0.595430*	0.191179*	0.999963*	–0.79671*
Δ	–	–	–	–	0.118124*	–
P	–	–	–	–	–	0.991866*
Φ	–	–	–	–	–	0.062327*
ARCH LM Test	0.905600	–	0.118900	0.003300	–	0.034300
AIC	1.183931	–	1.104628	1.420611	–	0.813535
SBC	1.193693	1.184393	1.118294	1.434277	–	0.829154
F Statistics	0.014041	0.030967	2.431730	8.633556	3.953776	4.483872
GARCH Models of Lead through ARMA (2,1)						
α_0(constant)	0.198735*	0.121329*	0.151288*	–0.77788	0.066601	0.317803*
(ARCH) A	–0.05096*	–0.05308*	0.083690*	–.56949*	–0.00361*	0.084945
(Asymm-int) ϑ	–	–	–0.15235*	–1.04709*	0.433020	–
β(GARCH)	–	0.409647*	0.502919*	0.227179*	0.963273	–0.364666
Δ	–	–	–	–	2.632507*	–
P	–	–	–	–	–	–0.262995
Φ	–	–	–	–	–	0.125051
ARCH LM Test	0.423200	–	0.180500	0.000400	0.698200	0.142200
AIC	1.163233	–	1.337942	1.417251	1.149084	1.410362
SBC	1.172994	1.169079	1.351609	1.430917	1.164703	1.425981
F Statistics	0.641153	0.485366	1.793393	12.70452	0.150209	2.153782
GARCH Models of Nickel through ARMA (2,1)						
α_0(constant)	0.211591*	7.08E–05*	5.06E–05*	–3.30478*	0.395436*	0.275862*
(ARCH) A	–0.05625*	0.015018*	0.018451*	–0.18671*	–0.09984*	0.118676
(Asymm-int) ϑ	–	–	–0.004528	0.099766*	0.618892*	–
β(GARCH)	–	0.983510*	0.983627*	–0.92353*	0.999907*	–0.40124*
Δ	–	–	–	–	0.113003*	–
P	–	–	–	–	–	–0.122867
Φ	–	–	–	–	–	0.042207
ARCH LM Test	0.6802	0.1209	0.1234	0.6032	0.0004	0.0000
AIC	1.218002	0.663841	0.664303	1.054864	0.776579	1.388445

1	2	3	4	5	6	7
SBC	1.227763	0.675555	0.677969	1.068531	0.792198	1.404064
F Statistics	0.169807	2.405597	2.374305	0.269983	12.74719	22.20573
GARCH Models of Zinc through ARMA (2,1)						
α_0(constant)	0.211430*	0.141747*	0.147383*	–0.86506*	0.375347*	0.210752*
(ARCH) A	–0.06268*	–0.06273*	–0.07405*	–0.60531*	–0.10382*	–0.05462*
(Asymm-int) ϑ	–	–	0.008396	–1.10934*	0.638136*	–
β(GARCH)	–	0.348651*	0.351129*	0.158449*	0.999770*	–0.77980*
Δ	–	–	–	–	0.126930*	–
P	–	–	–	–	–	–0.280897
Φ	–	–	–	–	–	0.000282
ARCH LM Test	0.2831	0.3235	0.3705	0.0263	0.0006	0.9260
AIC	1.203493	1.200318	1.203978	1.434055	0.825376	1.153219
SBC	1.213252	1.212029	1.217640	1.447718	0.840990	1.168834
F Statistics	1.151781	0.974442	0.801771	4.939108	11.91733	0.008624

Note: A = ARCH (1), B = GARCH (1, 1), C = TARCH (1, 1), D = EGARCH (1, 1), E = PARCH (1, 1), F = CGARCH (1, 1). At the 5% level of significance *.

Source: own elaboration.

From the result of the minimum AIC and SBC, maximum likelihood (ML) values, the models that can be accepted as best suiting are EGARCH (1,1) for Aluminum; GARCH for Nickel, while for PARCH (1,1) for Copper, Lead, Zinc. Apart from that, the values of the ARCH and GARCH parameters, i.e., (α) and (β) for all the models, are observed as positive and significant. This can be interpreted as the Indian base metal indices having ARCH and GARCH.

To confirm the existence of volatility asymmetric for the data series, it can be said from the value of (ϑ), i.e., from the EGARCG model. The outcomes confirm that all the data series show negative results except for Aluminum and Nickel. This negative result in the EGARCH interprets from the conditional variance equation that the return has an asymmetric response due to a positive value. This positive result of return outlays Commodity indices consists of the leverage effect, i.e., bad news brings volatility.

4. Discussion

From the result of the minimum AIC and SBC, maximum likelihood (ML) values, the models that can be accepted as best suiting are EGARCH (1,1) for Aluminum; GARCH for Nickel, while for PARCH (1,1) for Copper, Lead, Zinc. Apart from that, the values of the ARCH and GARCH parameters, i.e., (α) and (β) for all the models, are observed as being positive and significant. This can be interpreted as the Indian base metal indices having ARCH and GARCH.

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Conclusions

The study encompasses various symmetric and asymmetric models for volatility for identifying conditional volatility in Indian base metal indices for the first time from 2011 to 2022.

One of the most important intentions behind this study was to identify the presence of the effects of asymmetry in the commodity markets by implementing GARCH family models. The model shows that volatility clustering exists as the GARCH test's probability values are statistically significant.

Besides, the sum of α and β is less than one for all the commodity returns observed from models like GARCH, PARCH, and TARCH. This means the volatility sustains for a longer time, and it consumes a long period to reach the mean value. For instance, the sum of α and β for Aluminum and Nickel is high. This means the model for volatility measurement is accurate through the GARCH models.

The result of GARCH is found to be bigger in the case of aluminum and nickel, which means the returns of such are more dependent on their past variances compared to copper, lead, and zinc.

The study has revealed that the GRACH asymmetric models, while approximating and predicting the financial time series, can enhance the model's output when it has a high frequency. Here, the asymmetric GARCH models work better in predicting the volatility in comparison to classic models.

Regarding the valuations of the financial assets, it is wise to select the model that considers the long memory. This study shows that the GARCH, EGARCH, and PARCH models are considered the best-fitted models as the conditional volatility is more persistent for all the base metal indices.

Bollerslev *et al.* (1994) and Pagan (1996) opined the different results that are followed by many researchers and practitioners which is not true, so this study's outputs can be considered a rational approach for evaluation, i.e., the return series of Indian base metal indices have leptokurtic, Volatility clustering, Leverage effect, and long memory.

The findings of this study on Indian base metal indices highlight significant volatility clustering and leverage effects, which are essential for investors and policymakers. The selected GARCH family models, including EGARCH, GARCH, TARCH, PARCH, and CGARCH, effectively capture these dynamics. The presence of volatility clustering indicates the persistence of market trends, crucial for timing trades and hedging positions. Furthermore, the identification of leverage effects reveals the asymmetric response of base metal indices to positive and negative news, providing insights into market dynamics. These findings align with the Efficient Market Hypothesis, suggesting that market prices reflect available information but also demonstrate the influence of psychological factors on market behavior. Policymakers may consider implementing measures to manage volatility, such as circuit breakers, to stabilize market conditions and reduce investor risk. Future research could explore the impact of external factors on volatility and the effectiveness of different risk management strategies. Overall, this study contributes to a deeper understanding of financial market behavior and offers valuable insights for investors, policymakers, and researchers.

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