“Modeling asymmetric volatility of financial assets using univariate GARCH models: An Indian perspective”

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ARTICLE INFO	Neenu Chalissery, Mosab I. Tabash, Mohamed Nishad T. and Maha Rahrouh (2022). Modeling asymmetric volatility of financial assets using univariate GARCH models: An Indian perspective. *Investment Management and Financial Innovations*, *19*(4), 244-259. doi:10.21511/imfi.19(4).2022.20
DOI	http://dx.doi.org/10.21511/imfi.19(4).2022.20
RELEASED ON	Tuesday, 06 December 2022
RECEIVED ON	Wednesday, 12 October 2022
ACCEPTED ON	Tuesday, 22 November 2022

JOURNAL	"Investment Management and Financial Innovations"
ISSN PRINT	1810-4967
ISSN ONLINE	1812-9358
PUBLISHER	LLC “Consulting Publishing Company “Business Perspectives”
FOUNDER	LLC “Consulting Publishing Company “Business Perspectives”

NUMBER OF REFERENCES	NUMBER OF FIGURES	NUMBER OF TABLES
67	1	12

BUSINESS PERSPECTIVES

LLC "CPC "Business Perspectives"
Hryhorii Skovoroda lane, 10,
Sumy, 40022, Ukraine

www.businessperspectives.org

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MODELING ASYMMETRIC VOLATILITY OF FINANCIAL ASSETS USING UNIVARIATE GARCH MODELS: AN INDIAN PERSPECTIVE

Received on: 12th of October, 2022
Accepted on: 22nd of November, 2022
Published on: 6th of December, 2022

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Abstract

In recent years, numerous models with various amounts of variance have been developed to estimate and forecast important characteristics of time series data. While there are many studies on asymmetric volatility and accuracy testing of univariate Generalized Autoregressive Conditional Heteroscedasticity models, there are no parallel studies involving multiple financial assets and different heteroscedastic models and density functions. The objective of this study is to contrast the forecasting accuracy of univariate volatility models with Normal and Student-t distributions in forecasting the volatility of stock, gold futures, crude futures, exchange rate, and bond yield over a 10-year time span from January 2010 through December 2021 in Indian market. The results of exponential, threshold and asymmetric power models show that the volatility stock (–0.12047, 0.17433, 0.74020 for Nifty, and –0.1153, 0.1676, 0.7372 for Sensex), exchange rate (–0.0567, 0.0961,0.9004), crude oil futures (-0.0411, 0.0658, 0.2130), and bond yield (–0.0193, 0.0514 and –0.0663) react asymmetrically to good and bad news. In case of gold futures, an inverse asymmetric effect (0.0537, –0.01217, –0.1898) is discovered; positive news creates higher variance in gold futures than bad news. The Exponential model captures the asymmetric volatility effect in all asset classes better than any other asymmetric models. This opens the door for many studies in Indian financial market.

Keywords asymmetric volatility, financial assets, univariate Generalized Autoregressive Conditional Heteroscedasticity models, model comparison

JEL Classification C22, C52, C53, G17

INTRODUCTION

The three most common phenomena in time series analysis are volatility clustering, leptokurtosis, and asymmetric volatility (Aliyev et al., 2020). These types of time series characteristics have led to the development of numerous models with varying levels of variance for the estimation and forecasting of volatility. Lengthy periods of large market variance following a period of large variance, as well as long lengths of weak market variance following a period of weak variance, are called the volatility clustering (Cao & Tsay, 1992). A firm exhibits higher volatility asymmetry when future volatility is predicted by a negative return relative to a similar-sized positive return (Nelson, 1991). The main causes of this occurrence are the Risk Premium Effect (French et al., 1987) and Leverage Effect (Black 1976; Christie, 1982). The leverage effect theory put forth by Black (1976) argues that the general tendency for increases in return volatility to be adversely linked with changes in return of stock and that variability is typically large during market declines (bad news) than during market increases (good news). As evidenced by later studies by Christie (1982) and Schwert (1989),

Conflict of interest statement:
Author(s) reported no conflict of interest

http://dx.doi.org/10.21511/imfi.19(4).2022.20

the leverage effect is insufficient to describe this phenomenon. Even if the underlying market shocks have distributions that are conditionally normal, the volatility feedback can still explain these return characteristics.

When there is an asymmetric effect in time series data, the conditional variance is likely to have an asymmetric response to the good and bad news. The ARCH and GARCH models can estimate and predict the variance in the time series data in the majority of cases, but they fall short in capturing key crucial aspects of asymmetric behavior of the financial data. Many authors evaluated the asymmetric response of conditional volatility of various asset classes to negative (unfavorable) and positive (favorable) events/news. Even though, particularly with regard to an emerging market like India, no studies have investigated this effect by incorporating major financial assets in the Indian financial market together. The main goal of earlier studies in the Indian context was to fit a conditional variance model to a specific financial market, most frequently the stock market (Chandra & Thenmozhi, 2015), (Kumar & Dhankar, 2009), (Karmakar, 2007), and (Goudarzi & Ramanarayanan, 2011). Moreover, previous researchers have mostly concentrated on estimating the asymmetric effect in the volatility of a specific financial instrument or predicting the accuracy of univariate GARCH models. The most intriguing component, which has not been addressed by previous researchers, is measuring the asymmetry in the volatility of different financial assets using multiple univariate GARCH models. This work will add to this literature by incorporating different financial assets and multiple GARCH models. The asymmetric volatility features among stocks, commodities, forex, and bonds are being investigated for the first time in an Indian context using multiple GARCH family models with different density functions. This will be helpful for the research community to provide a summary of all those studies in this field. Further, it will help national and international investors construct their portfolios, thereby reducing investment risk by not depositing all eggs in a single basket.

1. LITERATURE REVIEW AND HYPOTHESES

As the financial market has undergone continuous upheaval as a result of financial crises and crashes, modeling asymmetric volatility using univariate GARCH models has drawn the attention of academics and researchers in recent years. The history of the asymmetric volatility effect is discussed in this section along with the methodology used by researchers for estimating it.

The empirical phenomenon of volatility asymmetry has been well studied by Black (1976), Christie (1982), and Schwert (1989), which means a decrease in the stock's value would raise financial leverage, making it riskier and more volatile, and vice versa. The leverage effect (Black 1976) was the initial justification for the asymmetric volatility, which indicates that a fall in the stock price reduces the equity's worth more than it does the debt's value, increasing the ratio of debentures to owner's fund, which raises the risk of the firm and causes volatility to rise. There are other reasons for the asymmetric volatility in addition to the impact of financial leverage, like short selling and behavioral preference (Talpsepp & Rieger, 2010) and asymmetric attention (Dzieliński et al., 2018). Kao (2021) claim that this impact has a more aggressive influence heuristic during overnight trading periods and validate the behavioral explanation for this effect.

Numerous authors have looked into the asymmetric volatility and leverage effect in various asset returns, including stock indices, foreign exchange returns, and various commodity price classes. In the empirical literature, the equity markets have received the most attention because they are where the effect is most pronounced. Asymmetric behavior of the Tel Aviv Stock Exchange was examined empirically by Alberg et al. (2008), together with other time series data characteristics with GJR and APARCH models. Further, Aliyev et al. (2020) used Exponential and GJR models to model and estimate the variability of Nasdaq-100; they found the presence of leverage effect and asymmetric volatility effect. The study suggests that the Exponential GARCH model with skewed Student-t density function is superior. This suggestion was confirmed by Maqsood et al. (2013) that the asymmetric GARCH models predict the leverage effect more precisely than symmetric models. By utilizing EGARCH, TGARCH, APARCH and IGARCH with normal and Student-t distributions (Abdullah et al., 2017) measured and predict currency volatility. Further, Cho and Rho (2022) used high-frequency data of the most transacted currencies to investigate the presence of asymmetry in the currency markets.

Further research into six main currencies realized semi-variances and variances, and the dynamics of interdependence between them on different frequency and temporal scales (Shahzad et al., 2020) revealed that the realized currency volatility and cross-currency impacts increased across financial crisis period. Hashmi et al. (2021) examined how this asymmetric volatility affects Indian trade across international borders with its top trading partners using a non-linear ARDL model; they proposed that the volatility of currency rate and international trade fluctuations in response to the financial crashes have an asymmetric relationship. Smales (2015) conducted research on asymmetric effect in the conditional volatility in gold futures and found that the sentiment of events had a significant influence on variability in return. Contrary to this, Todorova (2017), Chang et al. (2021), and Ghazali and Lean (2015) demonstrated empirical evidence for the gold market's inherent inverse asymmetric volatility effect and safe haven property. In addition, Chen and Mu (2021) and Tse (2016) looked at the inverse relationship among return and volatility of agricultural, energy, industrial, and precious metal commodities and discovered the "inverse leverage effect" with the exception of crude oil futures. For the crude oil futures, they found the presence of a significant leverage effect (Liu et al., 2021). For bond yield, de Goeij and Marquering (2006) and Yang et al. (2012) confirm the presence of asymmetric response of bond yield to news announcements with different signs.

In the context of India, researchers have focused on modeling asymmetric reaction of conditional variance of stock towards news with different sign with different GARCH models. Karmakar (2007) made an investigation using Nifty to characterize the heteroscedastic characteristics of the Indian capital market using the standard GARCH, EGARCH and EGARCH-in-Mean. The study provides evidence of volatility asymmetry in addition to time-varying volatility, clustering and persistence. In similar manner, Mahajan and Singh (2009), Kaur (2004), Kumar and Maheswaran (2012), and Padhi (2006) took into account symmetric and asymmetric GARCH models to determine volatility and to confirm the existence of an asymmetric effect. Chakraborty and Subramaniam (2020) focused on how investor behavior changed the return and variability in stock in the time of market crashes. They discovered that investor emotion influences stock performance at extreme quantiles. When the market returns to its fundamentals, higher sentiment is followed by lower future returns, whereas low sentiment results in fear-induced selling, which lowers returns. Further, using the Nonlinear ARDL model, Raza et al. (2016) and Kumar et al. (2021) examine the relation among the prices of different financial assets in the context of India and offer empirical proof of the existence of asymmetries among return and volatility of these asset classes. While analyzing these literatures, most of the studies in the Indian context have either focused on single financial market, especially stock market or applied single GARCH model.

The fundamental econometric tool used to estimate and forecast asset return volatility is conditional heteroscedastic modeling. Engle's (1982) seminal paper proposed the ground-breaking idea of using ARCH (Autoregressive Conditional Heteroscedasticity) processes to model time-varying volatility. He compares the current error term's variance to earlier error terms. According to empirical data, to represent the dynamic behavior of conditional variance, a higher ARCH order is required. Bollerslev (1986) created the Generalized Autoregressive Conditional Heteroscedasticity models to solve this issue by minimizing the infinity of estimated parameters. Since their distributions are symmetric, ARCH and GARCH models do not represent the stylized truth that negative (positive) news raises (decreases) volatility (Awartani & Corradi, 2005). Numerous non-linear GARCH models have been created to address this issue. The Asymmetric Power ARCH (APARCH) model by Ding et al. (1993), the Threshold GARCH (TGARCH) model by Glosten et al. (1993), and the Exponential GARCH (EGARCH) model Nelson (1991) have been suggested as these nonlinear ex-

http://dx.doi.org/10.21511/imfi.19(4).2022.20

tensions of GARCH can be used to solve the issue. Further, different density functions have been used to increase the prediction accuracy of models (Bollerslev, 1986; Bailie & Bollerslev, 1989).

Even though there are various univariate and multivariate GARCH models, the precision of these models in estimating the volatility and other characteristics of financial data is important, and it has been the subject of numerous studies. A comparison of the most popular linear and non-linear GARCH and how they handle asymmetry was highlighted by Hentschel (1995). The author found that the two ways the GARCH models treat asymmetry and transform the conditional standard deviation are different from one another. Using the GARCH, EGARCH, GJR-GARCH, and APARCH models with various density functions, Alberg et al. (2008) and Lin (2018) modeled and replicated well accepted aspects about conditional variance. The result indicates that the EGARCH outperforms other asymmetric GARCH models. Using quadratic GARCH, Campbell and Hentschel (1992) derived a model of volatility feedback in stock returns. In this line of research, Peters (2001) assessed the precision of GARCH (1,1), EGARCH, GJR-GARCH, and APARCH with different density functions, and Caporin and Costola (2019) used the News Impact Curve to estimate conditional volatility and confirmed that different GARCH models, the study result indicate that even though models estimate the asymmetry none of them capture leverage effect. Moreover, studies included various software applications that were used to calculate asymmetric volatility and their forecasting precision. Charles and Darné (2019) assessed estimation accuracy of eight software packages utilizing different distributions, as well as the precision of out-of-sample forecasting. They demonstrated that results varied depending on the software, particularly for t-ratios. Many extensions of linear and non-linear GARCH models have recently been introduced to finance literature. BenSada (2021) enhanced the estimation of good and bad volatility using new class of asymmetric heteroskedastic models. Further Catania (2022) introduces a novel volatility model that allows for a more accurate description of the leverage impact and its spread throughout the financial time series.

In recent years, modeling volatility, especially asymmetric volatility, is an interesting field of research, as the financial market is witnessed by frequent ups and downs. Similarly, accurate volatility models are essential for managing portfolios and risk hedging. By looking into the asymmetrical behavior of various financial markets, investors would be able to safeguard themselves from significant losses by spreading their funds across many markets. Even though there is a lack of empirical studies on estimating these volatility features in India. Similarly, most studies have examined the asymmetric volatility of single financial assets using univariate GARCH models, no studies have looked at this effect by utilizing multiple financial assets, different GARCH models, and density functions. The primary goal of the study is to estimate the asymmetric behavior of stock, bond yield, exchange rate, gold, and crude oil futures on the Indian financial market. The study is also aimed at comparing the effectiveness of the various univariate GARCH models and suggesting the accurate model to estimate the asymmetric effect. The main hypotheses of this study are:

H_1: *There is a significant presence of asymmetric volatility in stock indices in the Indian financial market.*

H_2: *There is a significant presence of asymmetric volatility in currency return in the Indian financial market.*

H_3: *There is a significant presence of asymmetric volatility in bond yields in the Indian financial market.*

H_4: *There is a significant presence of asymmetric volatility in crude oil futures in the Indian financial market.*

H_5: *There is a significant inverse asymmetric volatility effect in gold futures in the Indian financial market.*

H_6: *The EGARCH model outperforms any other GARCH models to model the asymmetric volatility effect in time series in the Indian financial market.*

H_7: *The precision of GARCH models is significant influenced by characteristics of density functions in the Indian financial market.*

2. METHODOLOGY

2.1. Data

This paper evaluates the asymmetric behavior in the volatility of bond, commodity, stock and currency market. Sensex and Nifty are considered to be a proxy for the stock market, 10-year bonds represent the bond market, INR/USD rate is a proxy for the currency market, and the commodity market is represented by gold and crude oil futures. The study uses daily closing price data of five financial assets such as SENSEX, NIFTY 50, INR/USD, bond, gold and crude oil futures from 2010 through 2021. The study uses return data, which are produced by dividing the price at time t (P_t) by the price from the previous day (P_{t-1}), then taking the logarithmic first difference. The details of the financial asset selected for the study and the source of data collection are described in Table 1.

Table 1. Description of data

Financial Market	Financial asset	Source of data collection
Bond market	10-year bond yield	Reserve Bank of India (RBI)
Commodity market	Gold futures	Multi Commodity Exchange (MCX)
	Crude oil futures	
Stock market	S&P CNX Nifty 50	National Stock Exchange (NSE)
	S&P BSE Sensex	Bombay Stock Exchange (BSE)
Foreign exchange market	INR/USD	Bureau of Indian Standard (BIS)

2.2. Methods

The fundamental econometric tools for estimating and predicting the volatility of asset returns are conditional heteroskedastic models. Since the development of ARCH model by Engle (1982) and their generalization by Bollerslev (1986), many improvements have been made to this method for modeling volatility. Various GARCH models used to forecast different volatility characteristics of study's variables have been discussed below.

2.2.1. *GARCH models*

The GARCH (p, q) model

To simulate and predict asset dynamics, ARCH and its extensions are frequently used. Building on Engle's work (1982), Generalized ARCH model was created by Bollerslev (1986). GARCH models can reflect the varied impacts of favorable and unfavorable news on conditional volatility. The variance in a general GARCH model is written as:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-j}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-1}^2, \qquad (1)$$

where $\sigma_t^{\,2}$ is the return residual, ε_t is the conditional variance, and α_0, α_1 and β_j are the parameters to be calculated. For the model to be valid, the α_0, α_1 and β_j must all have nonnegative values, and $\alpha_1 + \beta_j$ are expected to be less than 1. This is a necessary condition for the positive variance. Higher values of the α_1 coefficient in the financial data series indicate a higher response to market shocks in terms of volatility, while the larger coefficients of the βj coefficient indicate the presence of market shocks.

The GARCH-M model

The mechanism behind volatility feedback is not taken into consideration by the GARCH model. It captures the "GARCH-in-mean" model, also known as the GARACH-M model, proposed by Engle et al. (1987):

$$y_t = c + \xi h_t + u_t. \qquad (2)$$

Or capture the risk using the standard deviation of the series instead of variance. That is:

$$y_t = c + \xi \sqrt{h_t} + u_t. \qquad (3)$$

Here the risk of asset return with GARCH-M is captured using the standard deviation of the series. That is:

$$y_t = \varphi + \sum_{k=1}^{p} \theta_k h_{t-k} + \sum_{i=1}^{q} b_i u_{t-i}^2. \qquad (4)$$

2.2.2. *Asymmetric GARCH models*

The Exponential GARCH model

The EGARCH (1,1) allows for an asymmetric reaction of conditional volatility to good and bad news. Nelson (1991) created it with the straightforward specification as follows:

$$Mean\ equation = r_i = \mu + \varepsilon_t. \qquad (5)$$

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Variance equation

$$\ln\left(\sigma_t^2\right) = a_0 + \beta_1 \ln\left[\sigma_{t-1}^2\right] + \\ + a_1\left[\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| - \sqrt{\frac{2}{\pi}}\right] - \gamma\frac{\varepsilon_{t-1}}{\sigma_{t-1}}, \tag{6}$$

where γ explains the asymmetries. If γ < 0, it indicates that bad news causes more volatility than positive news, whereas γ >0 indicates that good news has a greater destabilizing effect. When γ = 0, there is no asymmetry.

The Threshold GARCH model (TGARCH)

The Threshold GARCH (TGARCH) is a similar approach to modeling the asymmetric effect put forth by Zakoian (1994) and further extended by Rabemananjara and Zakoian (1993). The conditional standard deviation is also treated in this model. They defined TGARCH as:

$$\sigma_t = \omega + \alpha\sigma_{t-1}\left[\left|\varepsilon_t\right| - c\varepsilon_t\right] + \beta\sigma_{t-1}, \tag{7}$$

$$\sigma_t = \omega + \alpha l\left[\varepsilon_{t-1} \ge 0\right]\varepsilon_{t-1} + \\ + \gamma l\left[\varepsilon_{t-1} < 0\right]\varepsilon_{t-1} + \beta\sigma_{t-1}. \tag{8}$$

If γ > 0, an asymmetry exists, indicating that the impact of news with positive and negative signs on conditional volatility is different. The unfavorable shocks' impulse ($\alpha + \gamma$), is higher than the favorable shocks' impulse (α), so the asymmetry is visible.

The Asymmetric Power ARCH model (APARCH)

Further, Ding et al. (1993) proposed the asymmetric power ARCH (APARCH) model as:

$$\sigma_t^\delta = \omega + \alpha\left[\left|\varepsilon_{t-1}\right| - \gamma\varepsilon_{t-1}\right]^\delta + \beta\sigma_{t-1}^\delta. \tag{9}$$

In which $\beta > 0$, $\alpha > 0$, and $\omega > 0$. The asymmetric effect is reflected by the parameter γ, with –1 < γ < 1. If the value of the γ is positive, then the model captures the asymmetric effect.

3. EMPIRICAL RESULTS AND FINDINGS

To obtain the stationary series, price data have been transformed into return data by using the below equation:

$$r_t = 100\left[\log\left(P_t\right) - \log\left(p_{t-1}\right)\right], \tag{10}$$

where P_t represents the assets' closing value on date t. As in Table 2, the return series satisfies the stationarity test using the ADF and PP tests.

Table 2. Stationarity test

Source: Authors calculation.

Assets	ADF Test		PP Test	
	t-statistic	Probability	t-statistic	Probability
Crude Oil	–17.016	0.0000	–17.286	0.0000
Gold	–54.470	0.0000	–54.403	0.0000
INR/USD	–68.376	0.0000	–67.678	0.0000
NIFTY	–53.872	0.0000	–53.898	0.0000
SENSEX	–51.319	0.0000	–51.336	0.0000
Interest Rate	–54.274	0.0000	–54.456	0.0000

Table 3 reports the summary statistics of the profitability of six assets. The mean return of stock indices is higher (Sensex = 0.00044, Nifty = 0.00041) as compared with other assets, followed by gold futures (0.00021). The standard deviation of two stock indices (Sensex and Nifty) was higher during the sample period. This indicates that even though stock indices provide higher returns, their variation (risk) is also higher. The interest and exchange rates show a negative skewness, and all the assets show leptokurtic as the kurtosis value is greater than three.

One frequently employs the Lagrange Multiplier test to determine whether ARCH effects exist. Regress the squared regression residuals $\hat{e}^2$ on their lags $\hat{e}_{t-1}^2$ to test for first order ARCH.

$$\hat{e}_{t-1}^2 = \gamma_0 + \gamma\hat{e}_{t-1}^2 + v_t. \tag{11}$$

The null hypothesis is: $H_0 = \gamma_1 = 0$ against $H_1 = \gamma_1 \neq 0$.

In the absence of an ARCH effect, $\gamma_1 = 0$, and the testing equation will fit the data poorly with a low R2 value. It is anticipated that, if there is an ARCH effect, the size of $\hat{e}^2$ will rely on its lagged values and that the R^2 will be quite high.

Table 4 depicts the result of the ARCH-LM test. Since all the LM values are statistically significant at a 5% significance level, the fact that the series has an ARCH effect on the residuals indicates that the variance of the return of the six assets se-

Source: Authors calculation.

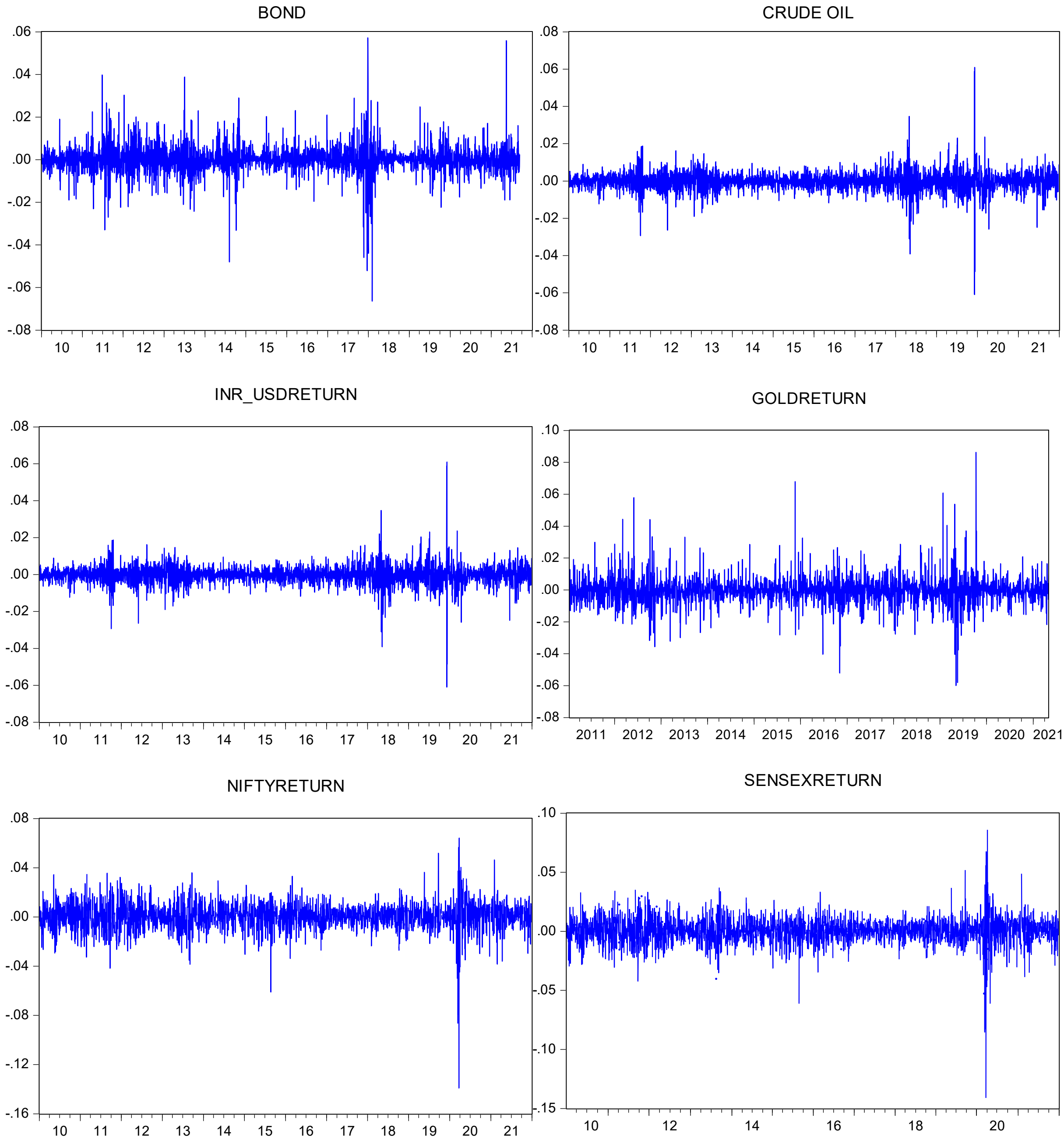

Figure 1. Return plot of financial assets

Table 3. Descriptive statistics

Source: Authors calculation.

Statistics	Interest rate	Gold futures	Crude oil futures	INR/USD	Nifty	Sensex
Mean	0.00005	0.00021	0.00003	0.00015	0.00041	0.00044
Maximum	0.05720	0.08469	2.24592	0.06097	0.1390	0.14101
Minimum	–0.06636	–0.05913	–2.21914	–0.06097	–0.084	–0.08595
Std. Dev.	0.00654	0.00895	0.00529	0.00525	0.01093	0.01093
Skewness	–0.25365	0.352466	0.563882	–0.10373	0.968786	1.054949
Kurtosis	17.2167	11.6296	10.191	25.0337	17.2723	19.8838
Jarque–Bera	25718.4	8387.005	11508.01	63320.99	25715.49	32389.44
Observations	3050	2685	2701	3130	2975	2685

http://dx.doi.org/10.21511/imfi.19(4).2022.20

ries is non-constant. In addition to this, volatility clustering was also observed on the return series (Figure 1).

Table 4. ARCH-LM test result

Source: Authors calculation.

Assets	ARCH-LM statistic	Prob. Chi Square (1)
Crude oil	27.027	0.0000
Gold	17.567	0.0000
INR/USD	83.781	0.0000
Nifty	93.040	0.0000
Sensex	88.026	0.0000
10-year bond yield	79.152	0.0000

Standard ARCH/GARCH models treat unfavorable news (Negative $e_{t-1} < 0$) and favorable news (Positive $e_{t-1} > 0$) symmetrically. However, the effect of news with different sign is asymmetric. Generally, when bad news affects the financial market, asset prices frequently go through a volatile period, and volatility rises and with a positive news, volatility tends to be small. This phenomenon is called as "leverage effect" (Black, 1976). Since the prevailing concern about the standard GARCH and GARCH-in-Mean models is unsatisfactory in accommodating the asymmetric volatility or leverage effect and volatility persistence, the study used asymmetric GARCH models, namely, EGARCH, TGARCH/GJR-GARCH, and APARCH, to accommodate these characteristics. Further, the comparative test of the univariate GARCH models for modeling asymmetric volatility of each asset return using Normal and Student-t distribution is described. The parameters used to evaluate performance include the Adjusted R^2 (High), Log likelihood (High), and SIC (Low).

Table 5 presents the estimation results of 10-year bond yield using univariate GARCH models. Except for APARCH, the leverage effect coefficients are significant with correct signs (-0.01933 for EGARCH and 0.05146 for TGARCH) under Gaussian/normal distribution. For APARCH, the sign of the coefficient is inverse and not significant. Therefore, the Exponential GARCH and Threshold GARCH models capture the asymmetric effect in interest rate. Among EGARCH and TGARCH, EGARCH is the accurate model as it has higher log likelihood and adjusted R^2 and low SIC value). Using the Student-t distribution, none of the asymmetric GARCH models is significant. Among symmetric GARCH models, the GARCH (1,1) model provides more accurate result than the GARCH-M model using Student-t distribution.

The estimation result of gold futures is summarized in Table 6. An inverse asymmetric effect or leverage effect is found for gold futures using normal distribution, that is, positive news creates more volatility in gold than negative news of the equal size, as the sign of leverage co-efficient γ is positive for EGARCH (0.0537) and negative for TGARCH (-0.0121) and APARCH (-0.1898), and significant for all the GARCH models. By analyzing the criteria for the best model (Adjusted R^2= 0.0017, Log Likelihood

Table 5. Estimation result of GARCH models: Bond yield

Source: Authors calculation.

Statistics	Gaussian distribution					Student-t distribution				
	GARCH (1,1)	GARCH–M	EGARCH	TGARCH	APARCH	GARCH	GARCH–M	EGARCH	TGARCH	APARCH
α_0	0.00005	0.00005	0.3461	0.00005	0.00114	0.00003	0.00003	0.3000	0.00003	0.0011
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0004)	(0.0000)	(0.0009)	(0.0000)	(0.0009)	(0.0001)
α_1	0.0892	0.0892	0.0246	0.0595	0.0118	0.0203	0.0203	0.0116	0.0724	0.0627
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
β	0.9062	0.9062	0.9601	0.9099	0.8988	0.9209	0.9208	0.9833	0.9210	0.9089
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
γ	–	–	–0.0193	0.0514	–0.0663	–	–	–0.0195	0.0378	0.0492
	–	–	(0.0005)	(0.0000)	(0.1008)	–	–	(0.1990)	(0.0616)	(0.6058)
Adj.R^2	0.0002	0.0003	0.0005	0.0001	0.00014	0.0005	0.0004	0.0003	0.0002	0.0002
Log Like	11476.83	11476.83	11527.35	11481.31	11541.17	11793.05	11793.04	11825.05	11794.18	11833.13
AIC	–7.524	–7.524	–7.557	–7.527	–7.565	–7.731	–7.311	–7.752	–7.731	–7.757
SIC	–7.512	–7.511	–7.545	–7.515	–7.552	–7.719	–7.717	–7.738	–7.718	–7.741
$\alpha_1 + \beta$	0.9954	0.9954	0.9847	0.9694	0.9116	0.9412	0.9411	0.9949	0.9934	0.9716
ARCH–LM	0.1317 (0.6969)	0.1517 (0.6969)	0.1448 (0.7035)	0.0614 (0.8043)	0.1358 (0.7125)	0.052 (0.8189)	0.0538 (0.8165)	0.0667 (0.7961)	0.0254 (0.8732)	0.0113 (0.9152)

= 9164.16, and SIC= -6.826), EGARCH is the precise model to estimate the inverse asymmetric effect of gold futures. Estimating asymmetric volatility using Student-t distribution, none of the asymmetric GARCH models provide significant results. Among symmetric GARCH models, GARCH (1,1) model provide more accurate result than the GARCH-M model under Student-t distribution.

The estimation result of crude oil futures was summarized in Table 7. A significant presence of asymmetric volatility effect is captured by all the non-linear GARCH models using Normal and Student-t distribution. Among the asymmetric GARCH models, EGARCH using Student-t distribution is a more accurate model to estimate the asymmetric variance in the crude oil futures, as it has a higher adjusted R^2 (0.0081) and log likelihood value (7030.04) and lower SIC value (-5.200).

In the case of the INR/USD rate, all the coefficients are significant with the correct sign (–0.0567 for EGARCH, 0.0961 for TGARCH) except for APARCH under both distributions (Table 8). For APARCH, the sign of the coefficient is positive but insignificant at the 5% level. Even though

Table 6. Estimation result of GARCH models: Gold

Source: Authors calculation.

Statistics	Gaussian distribution					Student-t distribution				
	GARCH (1,1)	GARCH–M	EGARCH	TGARCH	APARCH	GARCH	GARCH–M	EGARCH	TAGRCH	APARCH
α_0	0.00005	0.00004	0.7459	0.0006	0.0059	0.00001	0.00001	0.2021	0.00001	0.0092
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0019)
α_1	0.0148	0.0188	0.0358	0.0819	0.0287	0.1644	0.2507	0.1477	0.2782	0.2004
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0000)
β	0.8128	0.8403	0.9394	0.7837	0.8369	0.6019	0.6208	0.8119	0.6032	0.7012
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
γ	–	–	0.0537	–0.01217	–0.1898	–	–	0.0085	–0.0306	–0.0563
	–	–	(0.0000)	(0.0000)	(0.0000)	–	–	(0.7834)	(0.6591)	(0.5525)
Adj.R2	0.0013	0.0051	0.0017	0.0014	0.0009	0.0024	0.0007	0.0030	0.0024	0.0033
Log Like	9126.75	9129.96	9164,16	9137.66	9162.89	9462.741	9463.37	9417.03	0.9462.82	9474.99
AIC	–6.792	–6.793	–6.819	–6.799	–6.812	–7.041	–7.041	–7.046	–7.040	–7.049
SIC	–6.781	–6.780	–6.826	–6.786	–6.817	–7.028	–7.025	–7.031	–7.025	–7.031
$\alpha_1 + \beta$	0.8276	0.8591	0.9752	0.8656	0.8656	0.7663	0.8715	0.9596	0.8814	0.9016
ARCH–LM	0.0215	0.0015	0.1477	0.0051	0.1716	0.3871	0.3591	0.2621	0.3821	0.0328
	(0.8832)	(0.9688)	(0.7001)	(0.9805)	(0.6787)	(0.5339)	(0.5489)	(0.6085)	(0.5364)	(0.8561)

Table 7. Estimation result of GARCH models: Crude oil

Source: Authors calculation.

Statistics	Gaussian distribution					Student-t distribution				
	GARCH (1,1)	GARCH–M	EGARCH	TGARCH	APARCH	GARCH	GARCH–M	EGARCH	TGARCH	APARCH
α_0	0.00005	0.00005	0.2518	0.00004	0.00006	0.00005	0.00005	0.1916	0.00003	0.00008
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0000)
α_1	0.1029	0.1032	0.0885	0.0609	0.1001	0.1033	0.1028	0.0504	0.0286	0.0801
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
β	0.8889	0.8889	0.8857	0.9018	0.8099	0.8957	0.8952	0.8894	0.9203	0.9117
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
γ	–	–	–0.0411	0.0658	0.2130	–	–	–0.0675	0.1069	0.4553
	–	–	(0.0000)	(0.0000)	(0.0000)	–	–	(0.0000)	(0.0000)	(0.0000)
Adj.R2	0.0102	0.0102	0.0011	0.0012	0.0013	0.0051	0.0106	0.0081	0.0081	0.0080
Log Like	6918.78	6918.78	6927.94	6924.22	6928.09	7004.95	7009.40	7030.04	7023.60	7029.29
AIC	–5.118	–5.118	–5.125	–5.122	–5.124	–5.182	–5.185	–5.200	–5.195	–5.199
SIC	–5.104	–5.105	–5.112	–5.109	–5.109	–5.169	–5.169	–5.185	–5.180	–5.181
$\alpha_1 + \beta$	0.9918	0.9921	0.9742	0.9627	0.9100	0.9990	0.9980	0.9398	0.9489	0.9918
ARCH–LM	2.927	3.111	11.285	10.928	12.114	3.594	3.856	27.083	32.511	30.492
	(0.0871)	(0.0778)	(0.0818)	(0.0719)	(0.7005)	(0.6580)	(0.0796)	(0.781)	(0.782)	(0.612)

http://dx.doi.org/10.21511/imfi.19(4).2022.20

the EGARCH and TGARCH models capture the asymmetric volatility in INR/USD, the EGARCH provides a better forecast than the TGARCH model with an adjusted R^2 of 0.0108 and log likelihood value of 9806.40, and least SIC value of –8.548.

All the asymmetric GARCH models capture the asymmetric volatility effect for S&P CNX Nifty (Table 9) and BSE SENSEX (Table 10) return for the stock return. With regards to accuracy of models, the study found that the Exponential GARCH under Student-t distribution is the best to model asymmetric volatility of both stocks, as the Adjusted R^2 and Log likelihood values are higher (0.0086 and 9702.92 for Nifty and 0.0078 and 8809.41 for Sensex), and SIC value is minimum (-6.506 for Nifty and -6.543 for Sensex) as compared with TGARCH and APARCH.

One of the key goals of this study is to determine whether there is a single best model that captures asymmetric volatility across all assets. The result indicates that the Exponential GARCH model is best to captures the asymmetric volatility effect in all the asset classes than any other asymmetric GARCH model. In addition to this study tested how well GARCH models perform under different density functions. The log likelihood and SIC val-

Table 8. Estimation result of GARCH models: INR/USD

Source: Authors calculation.

Statistics	Gaussian distribution					Student-t distribution				
	GARCH (1,1)	GARCH–M	EGARCH	TGARCH	APARCH	GARCH	GARCH–M	EGARCH	TGARCH	APARCH
α_0	0.00003	0.00003	0.1306	0.00001	0.00002	0.00002	0.00006	0.0271	0.00005	0.00003
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0000)
α_1	0.0645	0.0645	0.0673	0.0126	0.0264	0.0575	0.1081	0.0781	0.0274	0.0508
	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0001)	(0.0285)
β	0.9150	0.9102	0.8925	0.9614	0.8483	0.8644	0.8404	0.8003	0.9136	0.8790
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
γ	–	–	–0.0567	0.0961	0.9004	–	–	–0.1113	0.1152	0.0123
	–	–	(0.0000)	(0.0000)	(0.2568)	–	–	(0.0000)	(0.0000)	(0.1201)
Adj.R2	0.0253	0.0253	0.0193	0.0195	0.0175	0.0112	0.0183	0.0108	0.0103	0.1030
Log Like	9672.07	9672.07	9666.87	9689.32	9688.21	9784.69	9789.34	9806.40	9803.46	9805.65
AIC	–8.449	–8.451	–8.444	–8.464	–8.462	–8.547	–8.550	–8.565	–8.563	–8.564
SIC	–8.432	–8.434	–8.429	–8.449	–8.445	–8.532	–8.533	–8.548	–8.545	–8.544
$\alpha_1 + \beta$	0.9795	0.9747	0.9598	0.9740	0.9107	0.9219	0.9485	0.8784	0.9410	0.9298
ARCH–LM	0.0406	0,0406	3.343	2.372	0.931	2.165	0.6694	11.608	7.292	7.617
	(0.8401)	(0.8401)	(0.0675)	(0.1235)	(0.3346)	(0.1059)	(0.4133)	(0.4213)	(0.0713)	(0.0658)

Table 9. Estimation result of GARCH models: NIFTY

Source: Authors calculation.

Statistics	Gaussian distribution					Student-t distribution				
	GARCH (1,1)	GARCH–M	EGARCH	TGARCH	APARCH	GARCH	GARCH–M	EGARCH	TGARCH	APARCH
α_0	0.000023	0.000027	0.2353	0.00015	0.00038	0.000026	0.000033	0.2389	0.000016	0.00061
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0000)
α_1	0.09354	0.10337	0.05820	0.0094	0.08287	0.0902	0.0145	0.0570	0.0086	0.0841
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
β	0.88700	0.87300	0.88744	0.90266	0.82051	0.8864	0.8653	0.8869	0.9019	0.8220
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
γ	–	–	–0.12047	0.17433	0.74020	–	–	–0.1216	0.17581	0.7624
	–	–	(0.0000)	(0.0000)	(0.0000)	–	–	(0.0000)	(0.0000)	(0.0000)
Adj.R2	0.00415	0.01859	0.0076	0.0071	0.0078	0.0083	0.0207	0.0086	0.0081	0.0081
Log Like	9618.56	9645.56	9673.46	9666.50	9673.64	9678.40	9682.53	9702.92	9694.99	9702.05
AIC	–6.4650	–6.4825	–6.5013	–6.4966	–6.5007	–6.491	–6.506	–6.520	–6.515	–6.519
SIC	–6.4549	–6.4704	–6.4892	–6.4845	–6.4866	–6.479	–6.501	–6.506	–6.501	–6.503
$\alpha_1 + \beta$	0.9805	0.9763	0.9456	0.9120	0.9033	0.9766	0.8798	0.9439	0.9105	0.9061
ARCH–LM	0.18943	0.08661	0.00110	0.22700	0.02886	0.1249	0.1376	0.2043	0.2041	0.1287
	(0.6636)	(0.7685)	(0.9735)	(0.6338)	(0.8651)	(0.7237)	(0.7106)	(0.6510)	(0.6510)	(0.9255)

Table 10. Estimation result of GARCH models: SENSEX

Source: Authors calculation.

Statistics	Gaussian distribution					Student–t distribution				
	GARCH (1,1)	GARCH–M	EGARCH	TGARCH	APARCH	GARCH	GARCH–M	EGARCH	TGARCH	APARCH
α_0	0.000209	0.000238	0.2339	0.000163	0.0004	0.00002	0.00030	0.2435	0.000017	0.000073
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.1174)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
α_1	0.0016	0.0090	0.05239	0.00811	0.08051	0.0869	0.0191	0.0519	0.0092	0.0819
	(0.0000)	(0.0000)	(0.0000)	(0.0028)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
β	0.89191	0.8802	0.88712	0.90427	0.82263	0.8902	0.8731	0.8861	0.9026	0.8227
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
γ	–	–	–0.1153	0.1676	0.7372	–	–	–0.113	0.1638	0.7391
			(0.0000)	(0.0000)	(0.0000)			(0.0000)	(0.0000)	(0.0000)
Adj.R2	0.0053	0.0155	0.0096	0.0085	0.0093	0.0047	0.0181	0.0078	0.0075	0.0078
Log Like	8731.17	8752.39	8779.11	8771.62	8778.80	8772.72	8791.05	8809.41	8801.61	8808.77
AIC	–6.5023	–6.5171	–6.5307	–6.531	–6.5363	–6.532	–6.545	–6.559	–6.553	–6.557
SIC	–6.4913	–6.5040	–6.5241	–6.518	–6.5209	–6.519	–6.530	–6.543	–6.537	–6.540
$\alpha_1 + \beta$	0.8935	0.8892	0.9394	0.9123	0.9031	0.9771	0.8922	0.938	0.9118	0.9046
ARCH–LM	0.31482	0.1235	0.09264	0.4772	0.1709	0.2191	0.1352	0.0945	0.4781	0.1305
	(0.5747)	(0.7252)	(0.7609)	(0.4897)	(0.6793)	(0.6397)	(0.7131)	(0.7585)	(0.4892)	(0.7179)

ue for models under Normal and Student-t distributions are listed in appendix Table A1 and Table A2. The comparison between bond yield and gold futures is not made because the outcome is insignificant under the student-t distribution. Models with Student-t distributions typically produce the highest Log likelihood and lower SIC value.

4. DISCUSSION

This study finds a significant presence of asymmetric volatility for all the assets except in the case of gold futures. The volatility stock, INR/USD, crude oil futures, and bond yield respond asymmetrically to positive and negative news. For all these assets, negative news creates higher variance than positive news of the equal size. This result supports the earlier findings of Goudarzi and Ramanarayanan (2011), Karmakar (2007), Jayasuriya et al. (2009), Alberg et al. (2008), Aliyev et al. (2020), Maqsood et al. (2013), and Umar et al. (n.d.) who proposed that the volatility of stock behave asymmetrically. While compared with earlier studies on comparing the accuracy of GARCH models to measure this asymmetry, the results are consistent with the findings of Alberg et al. (2008) and Maqsood et al. (2013), and contradict Srinivasan and Ibrahim (2010), and Sharma et al. (2021) who suggest that symmetric GARCH models are better for forecasting conditional volatility BSE SENSEX than the asymmetric GARCH model. Further, the estimation result of asymmetric volatility in bond yield supports the findings of de Goeij and Marquering (2006) and Yang et al. (2012).

In line with the results of Mensi et al. (2015), Bal et al. (2018), Shahzad et al. (2021), and Kumar Panda (2018), the findings affirm a significant presence of asymmetry in the conditional volatility of INR/USD rate. Supporting the earlier findings of the best GARCH model to capture the asymmetric effect in the exchange rate volatility (Balaban, 2004), this study confirms that the Exponential GARCH model is accurate. The estimation result of crude oil futures concurs with the results of studies by Sekati et al. (2020), Narayan and Narayan (2007), Todorova (2017), Liu et al. (2021), and Chiarella et al. (2016), who found a negative relationship between volatility and return of crude oil futures. In the case of gold futures, an inverse asymmetric effect is discovered; positive news creates more volatility in gold futures than negative news. The result is concordantly consistent with the findings of Todorova (2017), Chen and Mu (2021), and Ghazali and Lean (2015). However, the result supports the gold as a safe haven if its volatility falls during times of financial unrest (Jain & Biswal, 2016). This finding contradicts the findings of Smales (2015), who evidenced that bad news has a much bigger impact on the volatility of gold futures.

Based on Adjusted R, Log likelihood value, and SIC value, the study indicates that the Exponential GARCH is the best fit for modeling the asymmetric volatility of all financial assets. The result is

http://dx.doi.org/10.21511/imfi.19(4).2022.20

supported by previous studies by Maqsood et al. (2013), Alberg et al. (2008), and Lin (2018). While comparing the Gaussian and Student-t distributions, models based on the Student-t distribution are generally better fit. The data obtained concur with earlier studies by Hentschel (1995), Braun et al. (1995), Heynen et al. (2016), Alberg et al. (2008), Kanas (2000), and Luo and Wang (2019).

CONCLUSION AND IMPLICATIONS

The main objective of the study is to determine whether there is an asymmetric influence in the conditional volatility of the following six asset classes on the Indian financial market: bonds, gold futures, crude oil futures, INR/USD, Nifty, and Sensex using the Normal and Student-t density functions, and to assess the precision of the GARCH, GARCH-in-Mean, EGARCH, TGARCH, and APARCH models. The study finds that the volatility stock return (Nifty and Sensex), INR/USD, crude oil futures and bond yield behave asymmetrically. In case of gold futures, an inverse asymmetric effect is discovered. When comparing univariate GARCH models, based on diagnostic value, the study found that the Exponential model with Student-t distribution is better to capture the asymmetric volatility effect in all six asset classes. It can be concluded that except gold futures all other assets behave asymmetrically to news with different signs, and gold futures exhibit an inverse asymmetric response. With this, investors can combine assets with gold, so that investors can minimize risk of adverse of market conditions. Among the non-linear GARCH models, the exponential model captures this effect in the Indian capital market.

In the existing literature on asymmetric volatility in time series data, researchers have either focused on estimating the asymmetric effect in the volatility of a particular financial asset or forecasting the precision of GARCH models. This work is an addition to the body of knowledge on volatility by extending the research on estimating financial asset variability using univariate GARCH models and the accuracy of those models' forecasts. It expands our understanding of a useful GARCH family model for predicting market volatility. This provides a comprehensive grasp of asymmetric effect phenomenon in the assets under consideration. This evaluation is crucial for local and international investors to identify the diversification opportunity in the Indian stock market and the distribution of their financial resources. In addition, accurate volatility estimations are essential for portfolio management and risk hedging,. To generalize the findings, more research on modeling asymmetric volatility of various financial assets across different economic regions using univariate and multivariate GARCH models should be done in the future. Researchers can also employ alternative econometric models to simulate the asymmetric volatility effect in addition to GARCH models, and these models can be contrasted with GARCH models.

Like all other time series studies, this study has its limitations as it only focuses on a few specific assets, such as stocks, gold, crude, exchange rates, bond yields, and frequently used univariate GARCH models. In addition, the time frame of the study is limited to the 10-year period between 2010 and 2021.

AUTHOR CONTRIBUTIONS

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APPENDIX A

Table A1. Log likelihood comparison of different asymmetric models under Gaussian and Student-t distribution

Source: Authors calculation.

Statistics	Crude oil		INR/USD		Nifty		Sensex	
	Gaussian	Student-t	Gaussian	Student-t	Gaussian	Student-t	Gaussian	Student-t
GARCH	6918.78	7004.95	9672.07	9784.69	9618.56	9678.40	8731.17	8772.72
GARCH-M	6918.78	7009.40	9672.07	9789.34	9645.56	9682.53	8752.39	8791.05
EGARCH	6927.94	7030.04	9666.87	9806.40	9673.46	9702.92	8779.11	8809.41
TGARCH	6924.22	7023.60	9689.32	9803.46	9666.50	9694.99	8771.62	8801.61
APARCH	6928.09	7029.29	9688.21	9805.65	9673.64	9702.05	8778.80	8808.77

Table A2. SIC value comparison of different models under Gaussian and Student-t distribution

Source: Authors calculation

Statistics	Crude oil		INR/USD		Nifty		Sensex	
	Gaussian	Student-t	Gaussian	Student-t	Gaussian	Student-t	Gaussian	Student-t
GARCH	−5.104	−5.169	−8.432	−8.532	−6.454	−6.479	−6.491	−6.519
GARCH–M	−5.105	−5.169	−8.434	−8.533	−6.470	−6.501	−6.504	−6.530
EGARCH	−5.112	−5.185	−8.429	−8.548	−6.489	−6.506	−6.524	−6.543
TGARCH	−5.109	−5.180	−8.449	−8.545	−6.484	−6.501	−6.518	−6.537
APARCH	−5.109	−5.181	−8.445	−8.544	−6.486	−6.503	−6.520	−6.540