IJBARR
E- ISSN -2347-856X
ISSN -2348-0653

A STUDY ON ANALYZING VOLATILITY OF GOLD PRICE IN INDIA

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Abstract
Volatility in gold price has unembellished major problem to gold investors as excessive volatility does not leave anybody unaffected this lead togold investors to know more on volatility of gold price to invest more on gold.The market volatility is the result of various factors in the economy.The present study aims at measuringand forecasting gold price volatility. Based on an extensive literature survey, it was deciphered that there are issues that are left unaddressed in Indian market.For analyzing the secondary data, advanced financial econometric techniques are used namely, GARCH family techniques.The results report that the asymmetric model TGARCH (1.1)is found to be the best predictive model for modeling and forecasting volatility accurately with minimum errors.this will help the gold investor to safeguard their investments

Key Words: Gold Price Volatility, ARCH Model, Gold Investments.

Introduction

Since ancient times, gold was accepted as a universal means of the exchange (Tripathi, Parashar, & Singh, 2014). It is considered as a safe investment and used in large quantities during festivals and ceremonies in India. Gold has been a sizeable component of the portfolios of Indian households. The gold price seems to have an upward trend throughout, even during the recession and people use gold as a status symbol (Bhunia& Das, 2012). The price changes in gold affect almost every investor in India. Hence analysing the volatility of gold gained importance in the recent years (Tully &Lucey, 2007).
Volatility either positive or negative has brought with the fear in the minds of investors fraternity. Volatility is caused by many factors at economy level and firm level. This study primarily analyzes the effect of gold price volatility on the investor behaviour and studying how they make investment decisions during various market situations. The study focuses on the retail investors because it is them who higher concern about the uncertainty in receiving the expected returns as well as the variance in the returns.

Overview Of Auto Regressive Conditional Heteroskedasticity (ARCH) Models

The ARCH model was proposed by Engle (1982) and it is given as

Mean Equation

$$R_t = \alpha_0 + \alpha_1 R_{t-1} + \varepsilon_t \qquad (12)$$

Variance Equation

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_1 \varepsilon_{t-1}^2 \qquad (13)$$

Where, R_t is daily market returns, $R_{t-1}$is the conditional mean and $\varepsilon_t$is the error term of the mean equation that is serially uncorrelated with mean zero. The conditional variance of $\varepsilon_t$equals σ_t^2which is the function of q past squared returns and to be well defined ARCH model the parameters of conditional variance equation should satisfy $\alpha_0 > 0$ and $\alpha_1 \geq 0$.

Generalized Autoregressive Conditional Heteroskedasticity Model (GARCH Model)

Bollerslev (1986) proposed GARCH (p,q) model. According to this model the volatility at t is not only affected by the q past squared returns but also by p lags of past estimated volatility. In this study GARCH (p,q) model has been used that is even equivalent to ARCH(∞) and removed the problem of lags ‘p’. The specification of a GARCH (p,q) is given by

Mean Equation

$$R_t = \alpha_0 + \alpha_1 R_{t-1} + \varepsilon_t \qquad (14)$$

Variance Equation

$$h_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-1}^2 + \sum_{j=1}^{q} \beta h_{t-j} \qquad (15)$$

The parameter α_i captures the ARCH effect whereas β captures the GARCH effect in the model specified above. The GARCH model does not consider the asymmetric property of return i.e., negative relationship between the returns and conditional volatility.

To ensure positive variance parameter, GARCH model has certain restriction on the conditional variance parameter, these are $\alpha_0 > 0$, $\alpha_1 \geq 0$, $\beta \geq 0$, and $\alpha_1 + \beta = 1$

The basic GARCH is the symmetric model and that does not capture the asymmetry effect which is inherent in most of the stock markets return data series and this is also known as the 'leverage effect'. In the background of financial time series data analysis, the asymmetry effect refers to the characteristic of times series data on asset prices that 'bad news' tends to increase volatility more than 'good news' (Black, 1976; and Nelson, 1991). The EGARCH model and the TGARCH model proposed by Nelson (1991) and Glosten et al. (1993) respectively are explicitly intended to capture the asymmetry shock to the conditional variance in the return series of stocks and markets.

Exponential Generalized Autoregressive Conditional Heteroscedasticity (EGARCH) Model

Nelson (1991) proposed EGARCH model which permits the conditional volatility to have asymmetric relation with past information. Evidently, this impact happens when a surprising drop in price because of bad news rises volatility more than an unforeseen increase in price because of good news of comparable magnitude. This model communicates the conditional variance of a given variable as a nonlinear function of its own past values of standardized innovations that can respond asymmetrically to good and bad news (Drimbetas et al., 2007). In particular, Log likelihood ratio tests on an EGARCH model for p, q $\in$ (1, 2……..5) are employed orders to locate the most parsimonious EGARCH representation of the conditional variance of asset returns. The EGARCH (1, 1) model can be indicated as below:

Mean Equation

$$R_t = \beta_0 + \beta_1 R_{t-1} + \varepsilon_t \qquad (16)$$

Variance Equation

$$\ln(\sigma_t^2) = \alpha_0 + \alpha_1 \ln(\sigma_{t-1}^2) + \delta_1 \left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + \gamma_t \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \qquad (17)$$

Where, σ_{t-1}^2 denotes the estimate of the variance of the past time period that stands for the linkage between current and past volatility. In other words, it measures the degree of volatility persistence of conditional variance in the preceding period. $\frac{\varepsilon_{t-1}}{\sigma_{t-1}}$ represents information relating to the volatility of the past time period. It also signifies the magnitude effect (size effect) coming from the surprising shocks. $\frac{\varepsilon_{t-1}}{\sigma_{t-1}}$ specifies information relating to the leverage ($\gamma_1 > 0$) and the asymmetry ($\gamma_1 \neq 0$) effects. α's, β's, δ and γ are the constant parameters that needs to be estimated. ε_t represents the innovations distributed as a Generalized Error Distribution (GED), a special case of which is the normal distribution (Nelson, 1991).

ThresholdGeneralized Autoregressive Conditional Heteroskedasticity (TGARCH) Model

The TGARCH model was presented by Glosten et al. (1993) which detects the asymmetric in terms of negative and positive shocks and augments multiplicative dummy variable to check whether there is statistically significant difference when shocks are negative. In TGARCH model, it has been perceived that positive and negative shocks of even magnitude have a different impact on stock market volatility that may be acknowledged to a 'leverage effect' (Black, 1976). Likewise the negative shocks are followed by greater volatility than positive shocks of the similar magnitude (Engle and Ng, 1993). The conditional variance for the simple TGARCH model is defined by:

Mean Equation

$$R_t = u + bR_{t-1} + \varepsilon_t \qquad (18)$$

Variance Equation

$$h_t = \alpha_0 + \sum_{i=1}^{p} \beta_i u_{t-1}^2 + \sum_{j=1}^{q} \lambda h_{t-j} + \delta u_{t-1}^2 d_{t-1} \qquad (19)$$

Where, d_t takes the value of 1 if u_{t-1} is negative and otherwise zero. So "good news" and 'bad news' have a diverse influence. If δ> 0 the leverage effect exists and news impact is asymmetric if $\delta \neq 0$. The persistence of shocks to volatility is given by $\beta_i + \lambda_j + \delta/2$.

Finally, to choose the volatility model that models best the conditional variance of the selected market (S&P CNX Nifty and BSE Sensex) returns series, the Ljung-Box Q statistics on the standardized residuals and squared standardized residuals and the Lagrange Multiplier (ARCH-LM) test are used. Besides, the information criteria, namely minimum Akaike Information Criteria (AIC), minimum Schwarz Information Criteria (SIC) and the maximum Log-likelihood (LL) values are used to evaluate which model is more appropriate for modelling the market volatility.

Statement of The Problem

The amount of literature in the field of volatility modeling of gold price is limited. Most of the literature on gold price were on the causal relationship of gold price either on the stock market returns or on the macroeconomic variables. There are very few studies in the past which focused on the estimation of conditional volatility of gold price. As gold occupies an imporatnt place in almost every Indian's portfolio, it is imperative to estimate the conditional variance of the gold price in India. There were no studies in the literature which estimated the conditional volatility of gold price in India. This study attempts to model the conditional volatility of gold price in india

Objectives

1. To analyze the presence of volatility clustering in gold price volatility in India
2. To Measure , Model and forecast gold prices using econometric model.

Empirical Results

Measuring Volatility in Gold Prices

Figure 1 – Daily Closing Prices of Gold

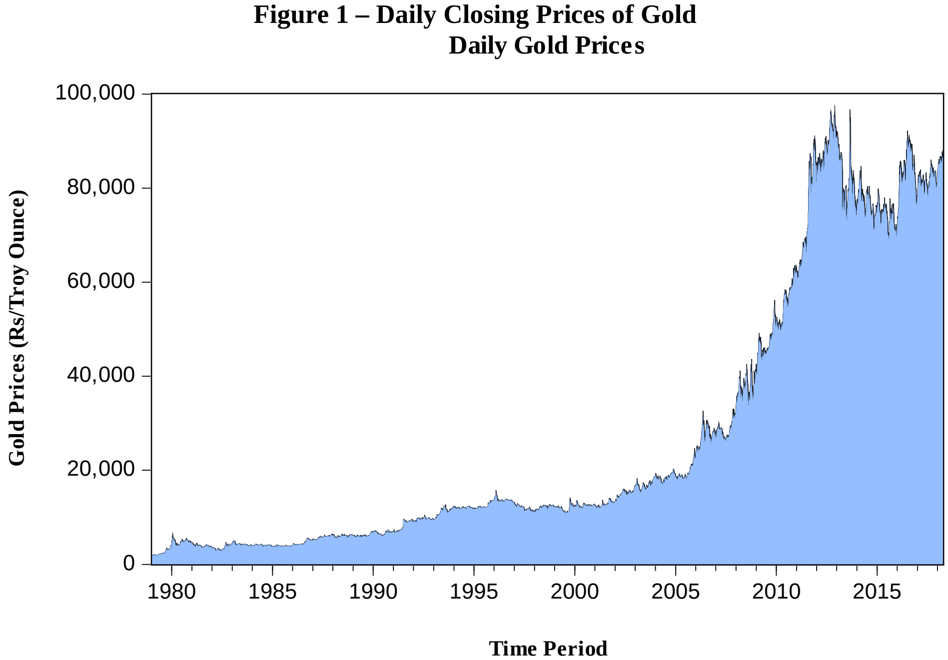
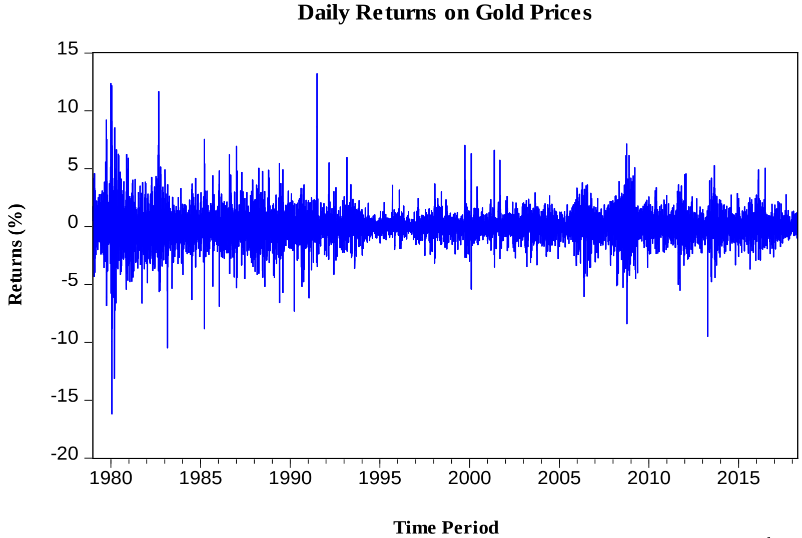


Figure 2 – Daily Returns on Golds



The figures 1 & 2 show the daily gold prices and its return for the study period starting from 2nd January 1979 to 13th April, 2018. The highest daily return from the gold was witnessed in 1981 and 1992 and the lowest daily returns were observed in 1980, 2008 and 2013. These higher and lower returns are because of the market volatility. Hence, one should be able to measure volatility and base their investment decisions accordingly to make better returns and counter volatility.

Modelling& Forecasting Gold Returns in India

In this section, the volatility in the gold returns has been modeled using both symmetric and asymmetric GARCH techniques. Further, the volatility has been forecasted for out of sample period while estimating various error coefficients.

Table 1 - Descriptive Statistics of Gold Returns in India

Statistics	Descriptive
Mean	0.037952
Standard Deviation	1.310861
Skewness	0.076291
Kurtosis	15.53860
Jarque-Bera	67141.39
P-value	0.000000
ADF (Intercept)	-112.3176*
ADF (Intercept and Trend)	-112.3149*
ADF (No Intercept and No Trend)	-112.2184*
PP (Intercept)	-112.4876*
PP (Intercept and Trend)	-112.4867*
PP (No Intercept and No Trend)	-112.3585*
KPSS (Intercept)	0.069069*
KPSS (Intercept and Trend)	0.063049*
Observations	10248

Note: Sample period is from January 2, 1979 to April 13, 2018. ADF, PP and KPSS represent Augmented Dickey–Fuller test, Phillips– Perron test and Kwiatkowski-Phillips-Schmidt-Shin respectively; * indicates significance at 1% level.

The distributional properties of Gold Price return series is assessed with the help of descriptive statistics and the same has been reported in table 1. The average returns of Gold in India are 0.04%. The standard deviation is found to be 1.31 that indicates higher fluctuation of daily returns of Gold. There is evidence that the return series is positively skewed and the kurtosis value is much higher than 3 indicating that the return distribution is fat-tailed or leptokurtic. The series is non-normal according to the Jarque-Bera test, which rejects normality at the one percent level significance. The daily return series of Gold in India is stationary at level. The stationarity test was conducted using the three unit root tests namely, ADF, PP and KPSS. This was tested with intercept, intercept and trend and with no intercept and no trend. For all these three tests, the daily return series found to be stationary at 1% level of significance.

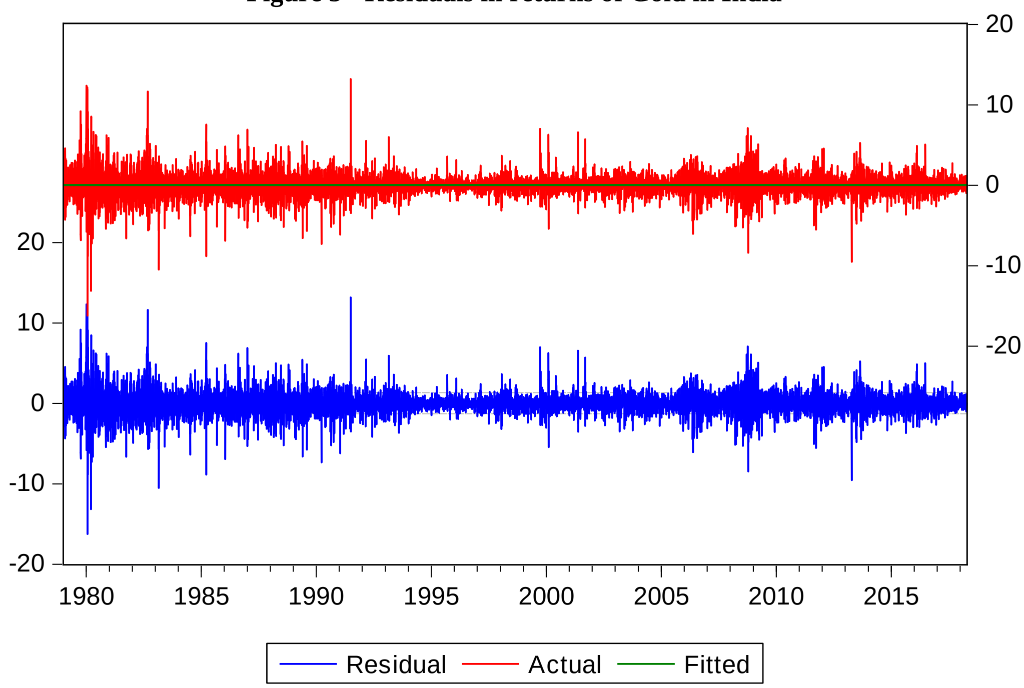
Table 2 - Autocorrelation and Heteroskedasticity Tests of Gold Returns in India

Test Statistics	Test Value	Prob. Value
Q(12) Statistics for Autocorrelation	135.27	0.000
Q^2(12) Statistics for Autocorrelation	4836.8	0.000
ARCH-LM Statistics for Heteroskedasticity	993.2484	0.000

Note: Ljung-Box (1978) Q-statistics for return and Q^2-statistics for the squared return series. They test for existence of autocorrelation in return series for 12 lags. L-Jung-Box test statistic tests the null hypothesis of absence of autocorrelation. Lagrange Multiplier ARCH-LM test statistic tests the null hypothesis of absence of Heteroskedasticity

Besides, the Table 2 shows that the Ljung-Box statistics Q(12) and Q^2(12) for the return and squared return series is highly significant at one percent level respectively, implying the evidence of autocorrelation in the return series. Hence we reject the null hypothesis that there is no autocorrelation in the daily return and squared return series at 1% level of significance. The Gold return shows evidence of ARCH effects as it is proved with ARCH-LM test meaning that there is the presence of Heteroskedasticity effect, i.e. volatility clustering and the same can be visual inspection of figure 7 that there exists the ARCH effect in the return series. In other words, the GARCH effect, i.e. time-varying second moment has been detected in the Nifty returns series as per the results of LM statistic. Thus the use of GARCH-type models for the conditional variance is justified for forecasting Gold returns.

Figure 3 - Residuals in returns of Gold in India



The residuals in the Gold returns confirms the ARCH and GARCH effect i.e., the clustering effect as the larger changes in the residuals are followed by the larger changes and the small changes are followed by the small changes confirming the volatility clustering. This testing and confirmation leads to conduct CHARCH type models for volatility modelling and its forecasting.

Table 3 - Results of Estimated GARCH (1,1) Model for Gold Returns

Estimates of GARCH (1,1) model					
$R_t = a_0+a_1R_{t-1}+\varepsilon_t(1)$ $h_t = \alpha_0 + \sum_{i=1}^{P} \alpha_i \, \varepsilon^2_{t-1} + \sum_{j=1}^{q} \beta_j \, h_{t-j}$ (2)					
a_0	**a_1**	α_0	**α_i**	**β_j**	**-**
0.017832 (2.024842)*	-0.083595 (-8.224998)*	0.016303 (15.29487)*	0.096415 (40.83962)*	0.900070 (409.7528)*	-
Q(12): 6.5258 **Q^2(12):** 5.8792 **ARCH-LM[5] Test:** 1.78462 **AIC:** 2.998625 **SIC:** 3.002155 **LL:** -15358.45					

Table 4 - Results of Estimated EGARCH (1,1) Model for Gold Returns

Estimates of EGARCH (1,1) model					
$R_t= \beta_0+\beta_1 R_{t-1}+ \varepsilon_t$ (3) $\ln(\sigma^2_t) = \sim_0 + \sim_1 \ln(\sigma^2_{t-1}) + \delta_1 \left\| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right\| + \gamma_1 \frac{\varepsilon_{t-1}}{\sigma_{t-1}}$ (4)					
β_0	β_1	α_0	α_1	δ_1	¥$_1$
0.036268 (4.088948)*	-0.087179 (-9.058209)*	-0.135677 (-47.50739)*	0.192795 (50.19695)*	0.043070 (17.08491)*	0.981472 (1063.816)*
Q(12): 9.2002 **Q^2(12):** 6.7345 **ARCH-LM[5] Test:** 3.52323 **AIC:** 2.990160 **SIC:** 2.994396 **LL:** -15314.08					

Table 5 - Results of Estimated TGARCH (1,1) Model for Gold Returns

Estimates of TGARCH (1,1) model					
$R_t = a + bR_{t-1} + £_t$ (5) $h_t = \sim_0 + \sum_{i=1}^{p} {}_i u^2_{t-1} + \sum_{j=1}^{q} ª_j h_{t-j} + ¢ u^2_{t-1} d_{t-1}$ (6)					
A	B	α_0	β_i	λ_j	δ
0.030215 (3.236965)*	-0.080997 (-8.073355)*	0.015178 (15.77375)*	0.116236 (31.79348)*	-0.053963 (-13.41316)*	0.906923 (451.6923)*
Q(12): 6.6290 **Q^2(12):** 4.2307 **ARCH-LM[5] Test:** 1.12378 **AIC:** 2.993289 **SIC:** 2.997525					

LL: -15330.11
Notes: Figures in parenthesis are z-statistics, * denote the significance at one level. Q(12) and $Q^2(12)$ represent the Ljung-Box Q-statistics for the model standardized and squared standardized residuals using 12 lags. AIC, SIC, and LL are Akaike Information Criteria, Schwarz Information Criteria and Log Likelihood respectively. ARCH-LM[5] is a Lagrange multiplier test for ARCH effects in the residuals up to 5 orders. (Engle, 1982).

Table 3, 4, & 5 shows the estimates of parsimonious GARCH (1,1), EGARCH (1,1) and TGARCH (1,1) models for daily gold return. The ARCH and GARCH terms in conditional variance equations are positive and significant at one per cent level in all estimations, implying a strong support for the ARCH and GARCH effects. Besides, table results show that the asymmetric coefficient γ_1 (0.981472) show that the gold returns in India exhibits statistically significant asymmetric effects at one percent level. This indicates that positive shocks have greater impact on this market than the negative shocks. In contrast, the result of TGARCH(1,1) model reveals that asymmetric effect captured by the parameter estimate δ (0.906923) which is greater than zero suggesting the presence of leverage effect, i.e. the volatility to positive innovations is larger than that of negative innovations.

The results of the diagnostic test show that the EGARCH models are correctly specified. The Q(12) and $Q^2(12)$ represent the Ljung-Box Q-statistics for the model standardized and squared standardized residuals using 12 lags and it confirms there is no autocorrelation in the residuals at 1% level significance. The Lagrange Multiplier (ARCH-LM) test was used to test the presence of remaining ARCH effects in the standardized residuals. With mean and variance equations of GARCH models being appropriately defined, there should be no ARCH effect left in the standardized residuals. The ARCH-LM [5] test for all the GARCH models indicate that there are any ARCH effects left in the standardized residuals of the variance equations and confirmed that there is no ARCH effect left in the residuals.

Table 6 - Model Selection for Gold Returns Volatility

Gold Returns			
Criteria	**GARCH (1,1)**	**EGARCH(1,1)**	**TGARCH(1,1)**
Akaike Information Criteria (AIC)	2.998625^3	2.990160^1	2.993289^2
Schwarz Information Criteria (SIC)	3.002155^3	2.994396^1	2.997525^2
LL	-15358.45^3	-15314.08^1	-15330.11^2
Rank	**3**	**1**	**2**
Superscripts (1), (2) & (3) denote rank of the model. The best p model has a rank 1.			

Since the diagnostic tests confirm the GARCH type models can be used for the modelling of the Gold return series and one has to select the preferred model based on AIC, SIC and LL statistics values criteria. The table 6 reveals the results of AIC, SIC and LL criteria. Bases on the results EGARCH (1,1) found to be preferred model as the values of AIC and SIC are minimum and the maximum value of LL for EGARCH (1,1) compared to other two models. Hence, EGARCH (1,1) is best model for modelling the volatility of S&P CNX Nifty return.

Table 7 - Forecast Performance of Estimated Models for the Out-of-Sample Period

Model	**GARCH (1,1)**	**EGARCH (1,1)**	**TGARCH (1,1)**
Root Mean Squared Error	0.501387^3	0.499488^1	0.500020^2
Mean Absolute Error	0.392744^3	0.391212^1	0.391666^2
Mean Absolute Percent Error	94.43957^1	95.57303^3	95.21008^2
Theil Inequality Coefficient	0.962057^3	0.928631^1	0.939127^2

IJBARR
E- ISSN -2347-856X
ISSN -2348-0653

Overall Rank	3	1	2
Note: Samples forecast from 1st January 2018 to 13th April 2018. Superscripts (1), (2) & (3) denote rank of the model. The best performing model has a rank 1.			

Most importantly, the models are evaluated in terms of their forecasting ability of future returns. We use the standard (symmetric) loss functions to evaluate the forecasting performance of the competing models: the Root Mean Squared Error (RMSE), the Mean Absolute Error (MAE), the Mean Absolute Percent Error (MAPE) and the Theil Inequality Coefficient (TIC). Table 7 shows the results of out-of-sample forecast performance of the estimated models. The model that exhibits the lowest values of the error measurements is considered the best one. The results show that EGARCH (1,1) model has outperformed all the other models in forecasting volatility of Gold return. This is followed by the TGARCH (1,1) model that performed the better in forecasting the conditional volatility of the Gold returns.

Conclusion

This study was conducted by applying GARCH model on the gold prices in India. This study was aimed at testing for the presence of asymmetric effect in the gold price volatility. Results indicate that the asymmetric EGARCH (1,1) model do perform better in forecasting conditional variance of the Gold returns in India rather than the symmetric GARCH model, confirming the presence of leverage effects. These findings are inconsistent with the evidence of Gokcan (2000) and Srinivasan (2011) as in their studies the best model for volatility modelling and forecasting was GARCH (1,1) model for market volatility.

References

1. Amado, C., & Terasvirta, T. (2014). Modelling Changes in the unconditional Variance of long stock return series. Journal of Empirical Finance, 25, 15-35.
2. Bapna, I., Sood, V., Totala, N.K. & Saluja, H.S. (2012). Dynamics of macroeconomic variables affecting price innovation in gold: A relationship analysi. Pacific Business Review International, 1-10. Bhattacharya,
3. Bhunia, A. & Das, A. (2012). Association between gold prices and stock market returns: Empirical evidence from NSE. Journal of Exclusive Management Science.
4. Bollerslev, T. (1986). Generalized autoregressive conditonal heteroskedasticity. Journal of Econometrics, 307327.
5. Gabaix, X., Plerou, P. G., & Stanley, H. E. (2005). Institutional Investors and Stock Market Volatility. NBER Working Paper No 11722, 1-50
6. K., Sarkar, N. & Mukhopadhyay, D. (2003). Stability of the day of the week effect in return and in volatility at the indian capital market a garch approach with proper mean specification. Applied Financial Economics.
7. Kaur, H. (2004). Time Varying Volatility in the Indian Stock Market. Vikalpa, 29(4), 25-42.
8. Khaparde, R., & Bhute, A. (2014). Role of Macroeconomic Performance on Stock Market Volatility: An Indian Perspective. International Journal of Management Research and Business Strategy, 3(1), 48-54.
9. Natchimuthu N, Ram Raj G, and Hemanth S Angadi(2017) is gold price volatility in india leveraged. Academy of Accounting and Financial Studies Journal 21(3),1-10.
10. Srinivasan, P. (2014). Gold price, stock price and exchange rate nexus: The case of India. The Romanian Economic Journal, 77-94.