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RESEARCH ARTICLE

PRICE VOLATILITY IN THE INDIAN GOLD SPOT MARKET: AN ECONOMETRIC ANALYSIS

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Abstract

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The present paper is an effort to examine the price volatility in the gold spot market. A host of Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models are used to analyze and gain a better understanding of the volatility of gold prices. The result of the GARCH (1, 1) model depicts that around 85% of the information associated with gold price volatility is derived from the previous days forecast. While the EGARCH model describes downward movement in gold daily return volatility is followed by higher volatility, the TGARCH (1, 1) model signifies that both positive and negative shocks have the same effect on future gold price volatility. This study has implications for both practitioners and academic researchers interested in price volatility in the gold spot market.

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Introduction:-

Gold is a precious metal with which mankind has a long and very intimate relation. Gold is considered as a symbol of purity and good fortune. Most of the gold that the entire world holds lies in India. There are many investment areas such as stock markets, mutual funds, fixed deposits and government bonds amongst others, but people still prefer to invest in gold. It is also used in various other ways like to make ornamental objects and jewelry, in electronics, in laptop computers, in aerospace, in glass making etc. Due to its appeal, gold has been historically priced above other commodities most of the time. The gold price history of the last 50 years is depicted in **figure no. 1** below.

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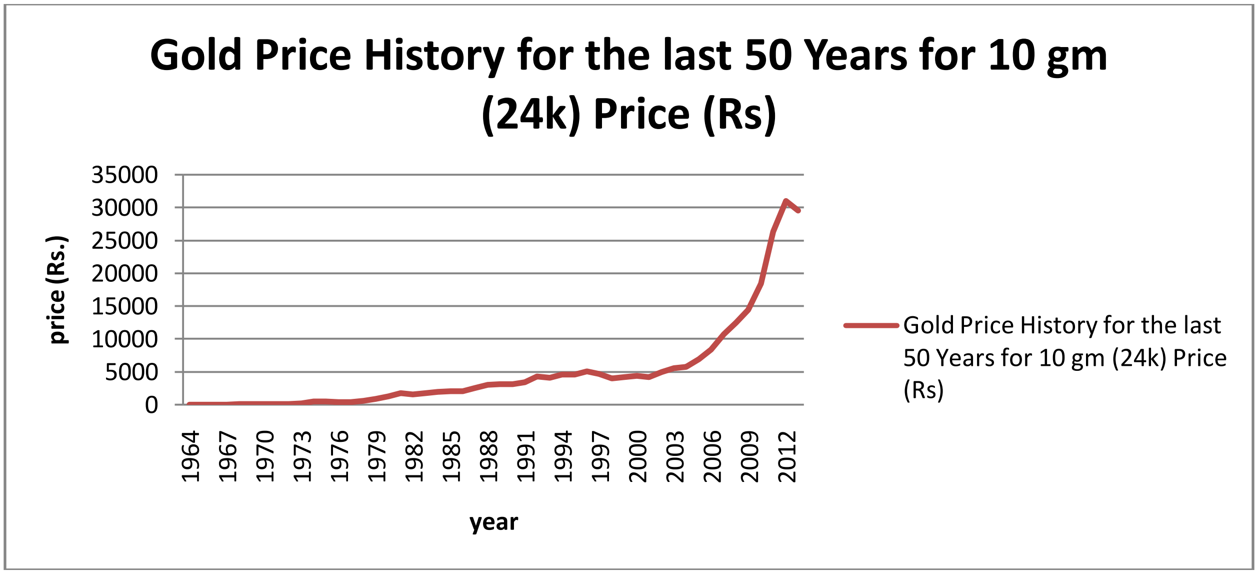
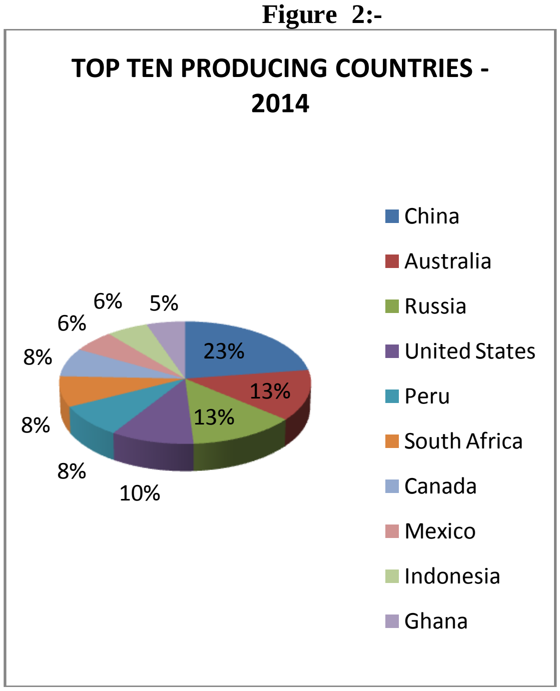


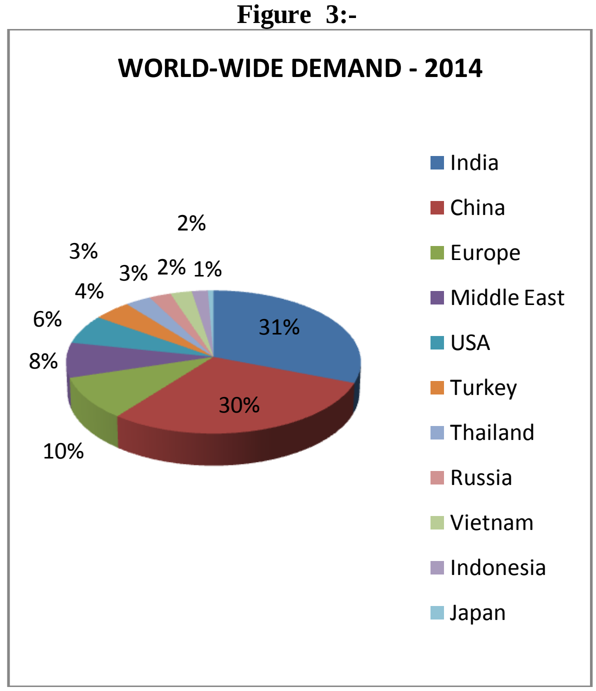
From the above graph it is clearly understood that the price of 10 gm of gold in the year 1964 was Rs.63.25 whereas in the year 2012 it was Rs.31, 050. The gold price of 10 gm in December 2013 was Rs. 29,600. Initially the increase in gold price was less from year to year but there is a drastic increase in the recent years. In the past decade, the increase in gold prices has been notable. However, a sudden jump in the price from Rs.18, 500 in 2010 to Rs. 26,400 in 2011 is an unpredictable increase. Various factors such as rise in investor demand, robust jewelry off take, geo-political concerns, US dollar movement against other currencies, Indian rupee movement against the US dollar, central banks diversifying into bullion, fall in supply, gold mine production etc influence gold prices in any country. In India, demand of gold and inflation are the two major factors which are responsible for gold price changes. The gold price variation can also be better understood by analyzing the demand and supply scenario of it in the country. The following figures i.e. figure no. 2 and figure no. 3 depict about the state of world wide supply and demand situation of gold by 2014 respectively.

Figure 2:-



Source: LBMA, Thomson Reuters GFMS

Figure 3:-



Source: World Gold Council

From the above figure it can be clearly understood that there is a mismatched scenario for supply and demand of gold in India. Though India stood first so far as demand for gold in the world is concerned with 31%, but does not stand even with in 10 highest gold producing countries of the world. Thus, it can be easily expected that the price of gold in the country mostly depends on the international market condition.

Having understood the importance of gold and its fluctuating price trend in the country, this paper is developed to analyze and gain a better understanding of the time varying dynamics of price volatility in the gold spot market. The present paper used three models from the ARCH family such as GARCH (1, 1), EGARCG (1, 1), and TGARCH (1, 1) model which are applied to the spot price of gold for a period of 5 and ½ years. When referring to the (1, 1) in each model, the first (1) represents the first order auto regression GARCH term and the second (1) represents the first order moving average ARCH term. In other words, the models suggest that future conditional variance is based on the past variance.

The outline of the paper is as follows. The next section briefly reviews the related literatures and discusses the contribution of this study. Section III and IV describes about the objectives and hypothesis of the study. Section V and VI explain about the data collection procedure and application of statistical tools. While section VII represents the empirical results of the applied tools, the final section summarizes the main findings of the study in form of conclusion.

Review of Literature:-

This section provides brief review of earlier studies on price volatility in commodity markets. There are numerous studies that analyses the price volatility in the developed countries. However, such studies are not enough in number in developing countries like India. There are few researches in which the researchers have examined commodity price volatility from different perspectives. This study will add to existing literature by understanding the price volatility allied with gold spot market.

Charles, Darne, and Kim (2014) tested the weak form market efficiency for gold, platinum and silver. They used daily spot data repossessed from Thomas Financial Data Stream for a period of 37 years i.e. from 1977 to 2013 and employed the automatic portmanteau and automatic variance ratio test. They suggested that the gold and silver markets displayed a downward trend of predictability representing that gold and silver markets have become more efficient over time.

Nawaz and Moomal (2012) conducted a study on the volatility in gold price returns. The data for the study collected on daily basis for a tenure of 3 years starting from 1st January, 2009 to 31st September, 2011. The results investigated volatility by using models such as standard deviation and GARCH and found an unequal spread of residuals referred as heteroskedasticity. Furthermore, a fast mean reversion has been observed showing that the alpha and beta are far from 1. Based on results it was concluded that there has been volatility in gold prices.

Coudert, Virginie and Raymond, Helene, (2011) examined the role of gold as a harmless haven. They extended the existing writings in 2 means. First, they studied crunch 7 stages consecutively distinct by recessions and bear markets. Second, ARMA-GARCH-X model had been used to evaluate conditional co-variances between gold and stocks returns. The regressions were run on monthly data for gold and numerous stock market indices. The study indicated that gold succeeded as being a safe haven against all the stock indexes. The outcome demonstrated that it holds for crunches named as recessions or bear markets, as the covariance between gold and stocks returns is observed as negative or null in all circumstances.

Marzo, Massimiliano and Paolo Zagaglia, (2010) examined how the connection of gold prices and the U.S. Dollar had been impacted by the current anarchy in financial markets. They have used spot prices of gold and spot bilateral exchange rates against the Euro and the British Pound to analyze the pattern of instability spillovers. They have also used the GARCH models to judge the causal links of instability fluctuates in the two assets. They recognized the capability of gold to produce constant co-movements with the Dollar exchange rate which have continued the latest levels of market disruption. Their results even disclosed that exogenous rise in market insecurity have inclined to generate reactions of gold prices that are extra steady than those of the U.S. Dollar.

Elder and Serletis (2008) used daily data from the New York Mercantile Exchange on spot-month futures prices for crude oil, gasoline, heating oil, natural gas, and propane. The time frame for the study was from 3rd January, 1984 to 30th June, 2005. They found that the energy prices displayed long memories and anti-persistence, as well as the variance of each commodity series being dominated by high frequency components. This indicates that the time series for sample commodities propose weak form inefficiency.

Kat and Oomen (2007) examined the return properties of 142 commodity futures from January 1965 to February 2005 using a multivariate analysis framework. The study suggested that the volatility of commodity futures is comparable to that of US large cap stocks. It is also found that a consistently positive risk premium is lacking in commodity futures with an exception of energy. They also recommended that futures returns and volatility can vary considerably over different phases of the business cycle for many commodities under different monetary conditions. Furthermore, in almost all commodities they found significant degrees of autocorrelation, which affects the properties of longer horizon returns.

Adrangi et al. (2006) investigated price discovery on nearby future prices of various commodities listed on Chicago Board of Trade (CBT). Using the daily closing prices of contracts from 1969 to 1999 obtained from CBT, the researchers found that there is an existence of strong bidirectional causality in futures prices.

From the above literature review, it is observed that there are enormous amount of literature on the concerned subject considering the world-wide commodity market. However, it is comparatively less in case of price volatility in Indian commodity markets. In such circumstances, this study carries a significant importance to re-look on the price volatility in gold spot market in India. Therefore, the broad objectives of this study are mentioned below.

Objective of the study:-

The principal objective of this study is to evaluate the price volatility in the Indian gold spot market. To accomplish this basic objective, following sub-objectives are set:

1. To analyze the gold spot price trend during last 5 decades.
2. To analyze the presence of volatility clustering in the gold spot price trend during 2011–16.
3. To analyze the time varying volatility in the gold spot prices during 2011-16.

Hypothesis:-

(H_0): Future conditional variance in gold spot price is not based on the past variances.

(H_1): Future conditional variance in gold spot price is based on the past variances.

Data and Methodology:-

The present study is based on the secondary data of daily cash (spot) prices of gold collected from www.mcxindia.com for the periods January 1, 2011 to June 30, 2016. The data includes 1484 observations and various statistical tools like ARCH, GARCH, EGARCH and TARCH are employed to analyze the time varying volatility in the gold spot price. Further, the application of three GARCH models requires the data to be stationary. In order to test the stationary of the data, the Augmented Dickey-Fuller test (1981) is performed. If the results indicate that the data are non-stationary, then the data will be transformed by taking the first difference of the daily spot price. The daily return series is used in all three GARCH models and calculated as $R_t = \ln(P_t/P_{t-1})$. All these tests are conducted using E-views software (version-8). A brief description about all these statistical tools is given below.

Augmented Dickey-Fuller Test (ADF):-

Augmented Dickey Fuller test (ADF) is used for detecting the presence of stationarity in the series. The early and pioneering work on testing for a unit root in time series was done by Dickey and Fuller (1979 and 1981).If the variables in the regression model are not stationary, then it can be shown that the standard assumptions for asymptotic analysis will not be valid. For a return series R_t, the ADF test consists of a regression of the first difference of the series against the series lagged k times as follows:

$$\Delta r_t = \alpha + \delta r_{t-1} + \sum_{i=1}^{p} \beta_i \Delta r_{t-i} + \varepsilon_t$$

$$\Delta r_t = r_t - r_{t-1}; r_t = \ln(R_t)$$

The null hypothesis is H_0: $\delta = 0$ and H_1: $\delta < 1$. The acceptance of null hypothesis implies nonstationarity. The nonstationary time series can be transformed to stationary time series either by differencing or by detrending.

Arch and garch model:-

ARCH and GARCH models assume conditional heteroscedasticity with homoscedastic unconditional error variance. It means the changes in variance are a function of the realizations of preceding errors and these changes represent temporary and random departure from a constant unconditional variance. The advantage of GARCH model is that it captures the tendency in financial data for volatility clustering. Therefore, it enables to make the connection between information and volatility explicit since any change in the rate of information arrival to the market will change the volatility in the market. In empirical applications, it is often difficult to estimate models with large number of parameters such as ARCH (q). To outwit this problem, Bollerslev (1986) proposed GARCH (p, q) models. The conditional variance of the GARCH (p, q) process is specified as

$$h_t = \alpha_0 + \sum_{j=1}^{q} \alpha_j \varepsilon_{t-j}{}^2 + \sum_{i=1}^{p} \beta_i h_{t-i}$$

with $\alpha_{0>}$ 0, α_1, α_2….., $\alpha_q \geq 0$ and β_1, β_2, ……, $\beta_p \geq 0$ to ensure that conditional variance is positive. In GARCH process, unexpected returns of the same magnitude produce same amount of volatility. The large GARCH lag coefficients indicate that shocks to conditional variance takes a long time to die out, thus volatility is 'persistent. If $(\alpha + \beta)$ is close to unity, then a shock at time t will persist for many future periods. A high value of it implies a 'long memory.'

Exponential GARCH (EGARCH) Model:-

GARCH models successfully capture thick tailed returns and volatility clustering, but they are not well suited to capture the "leverage effect" since the conditional variance is a function only of the magnitudes of the lagged residuals and not their signs. In the EGARCH model of Nelson (1991) $\sigma_t{}^2$ depends upon the size and the sign of lagged residuals. The specification for the conditional variance is:

$$\log(\sigma_t{}^2) = \alpha_0 + \sum_{j=1}^{q} \beta_j \log(\sigma_{t-j}{}^2) + \sum_{i=}^{p} \alpha_i \frac{|\varepsilon_{t-i}|}{|\sigma_{t-i}|} + \sum_{h=1}^{r} \gamma_h \frac{\varepsilon_{t-h}}{\sigma_{t-h}}$$

Note that the left-hand side is the log of the conditional variance. This implies that the leverage effect is exponential, rather than quadratic and that forecasts of the conditional variance are guaranteed to be nonnegative thus eliminating the need for parameter restrictions to impose non-negativity as in the case of ARCH and GARCH models. The presence of leverage effects can be tested by the hypothesis that $\gamma_h < 0$. The impact is asymmetric if $\gamma_h{}^1 = 0$.

Threshold GARCH (TARCH) Model:-

In ARCH / GARCH models both positive and negative shocks of same magnitude will have exactly same effect in the volatility of the series. T-GARCH model helps in overcoming this restriction. TARCH model was introduced by Zakoin (1994) and Glosten, Jaganathan and Runkle (1993). The generalized specification for the conditional variance is given by:

$$\sigma_t{}^2 = \alpha + \sum_{j=1}^{q} \beta_j \sigma_{t-j}{}^2 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}{}^2 + \sum_{h=1}^{r} \gamma_h \varepsilon_{t-h}{}^2 d_{t-h}$$

Where, $d_t = 1$ if $\varepsilon_t < 0$ and zero otherwise. In this model, good news, $\varepsilon_{t-1} > 0$ and bad news $\varepsilon_{t-1} < 0$, have differential effect on the conditional variance; good news has an impact of α_i, while bad news has an impact of $\alpha_i + \gamma_i$. If $\gamma_i > 0$, it indicates bad news increases volatility, and it can be said that there is a leverage effect for the i-th order. If $\gamma_i^1 = 0$, then the news impact is asymmetric. The main target of this model is to capture asymmetries in terms of positive and negative shocks.

Forecasting Evaluation:-

Serial correlation test, ARCH effect test and Normality test are employed to measure the accuracy of the forecasting models.

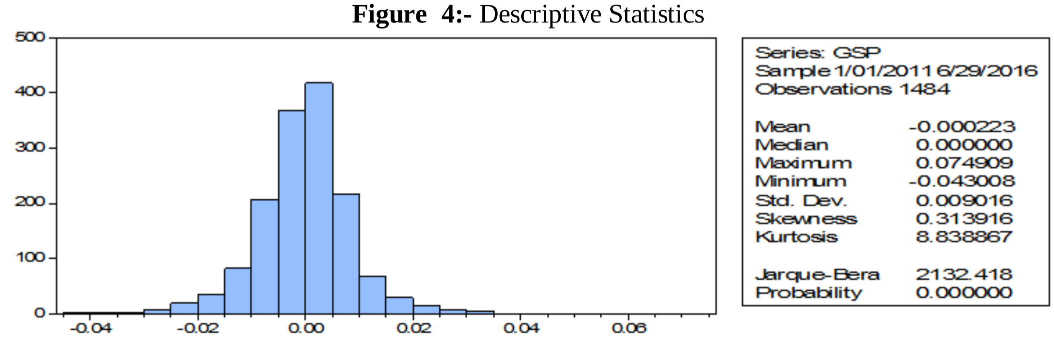
Analysis and Description:-

To examine the time varying volatility in the gold spot market, the various models of ARCH family like GARCH (1, 1), EGARCH (1, 1) and TARCH (1, 1) are analyzed. The present section begins with a preliminary statistical analysis of the data followed by an empirical analysis of each model. Finally, robustness checks are conducted to ensure that all GARCH models are correctly specified.

Descriptive Statistics:-

Figure 4 below displays a summary of descriptive statistics along with histogram for gold spot price returns from January 2011 to June 2016.

Figure 4:- Descriptive Statistics



From the above figure it is clearly understood that the mean gold return is -0.000223. The standard deviation is .009016. It can be seen that the gold price return varies from -0.043008 to 0.074909 stating that there is wide fluctuation in the daily return on gold price. The histogram displays the positive value for skewness at 0.313916 indicating the series distribution is skewed to the right. So far as kurtosis is concerned, gold price returns have a high peak and thicker tails than a normal distribution. Further, the Jarque-Bera test rejects normality at 5% level which indicates that the gold price returns are not normally distributed.

ADF Test:-

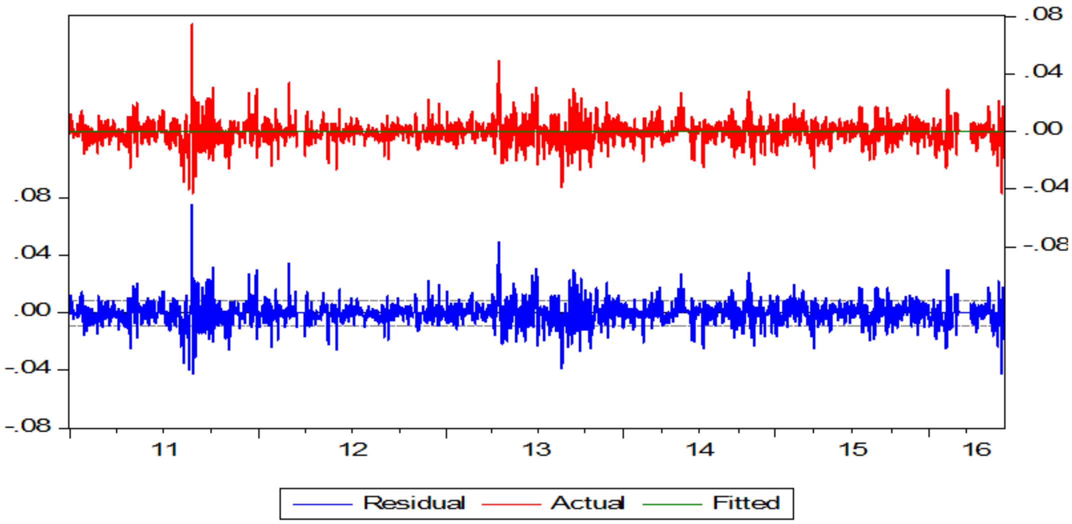
To examine the time varying volatility in the gold spot market, application of ARCH family models are required. But, for the estimation of ARCH and GARCH models, the variable is required to be stationary. The Augmented-Dickey Fuller (ADF) test is a statistical procedure which examines for the presence of unit roots in time series data. The daily gold return data used in the study are found to be stationary as referenced in table 1 below (Annexure 1).

Table 1:- ADF Unit Root Test

Particulars	t- statistics	Probability
At level	-38.92274	0.00

Before employing ARCH family model, it is also necessary to examine the 5 and ½ year time series of conditional variance estimates from January, 2011 to June, 2016. Figure 5 below depicts the periods of high and low volatility in the daily gold returns during the sample period.

Figure 5:- Conditional Variance of Gold returns



It can be clearly noticed from the above graph that there are several periods of low volatility followed by periods of low volatility for a prolonged period and periods of high volatility followed by periods of high volatility for a prolonged period. During the year 2011, it can be seen that for number of times period of low volatility followed by another period of low volatility and it continues till the first quarter of 2012. From mid of 1 quarter of 2012 to last quarter of the year, number of high volatility periods followed by high volatility periods. During this period, the volatility is extreme and peaks near .08 and then reverts to .01. Further, the periods of low volatility continues from 1st quarter of 2013 to 3rd quarter of 2013. Thereafter, the period of high volatility starts again. Thus, it can be concluded that figure 5 indicates about the time varying nature of the time series. This kind of volatility pattern for residuals gives sufficient justification to run ARCH family models like GARCH, EGARCH and TGARCH. Further, the whole thing can be double checked by appointing ARCH test to examine the application of ARCH family model to the time series under study. The result of ARCH test presented in Annexure -2 depicts that the observed R square is 105.17 and corresponding P value is 0.00 meaning that the null hypothesis of no ARCH effect can be rejected at 1% confidence level and alternative hypothesis of presence of ARCH effect can be accepted. It implies clustering of volatility where large changes tend to be followed by large changes, of either sign and small changes tend to be followed by small changes.

The GARCH Models:-

GARCH (Generalized Autoregressive Conditional Heteroskedasticity) models help to forecast volatility when volatility changes over time. This concept is known as heteroskedasticity. It is a common finding in almost all financial time series data that they do not exhibit homoscedasticity and is therefore, changing over time. In the present study the daily gold return data also follow the same pattern and changing over time. Therefore, the employment of GARCH, EGARCH and TARCH models to evaluate time varying volatility in daily gold return series as well as various factors influencing such volatility is legitimate.

The GARCH (1, 1) is the most popular model used when modeling daily returns (Taylor, 2005). Table 2 below displays the results of the GARCH (1, 1) model. (Annexure 3)

Table 2:- GARCH (1, 1) Model.

Dependent Variable: Spot returns in Gold				
Method: ML - ARCH (Marquardt) - Normal distribution				
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)				
Mean Equation				
	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.000104	0.0002	-0.51733	0.6049
Variance Equation				
C	3.67E-06	7.13E-07	5.143865	0.0000
Residual Term	0.106173	0.01227	8.651586	0.0000
GARCH Term	0.850975	0.01793	47.46546	0.0000

The results indicate that both ARCH term and GARCH term at 0.106 and 0.851 respectively are significant at the 99% level of confidence. These two parameters when combined equate to 0.957 which is close to unity. It implies that a shock at time t will persist for many future periods or it has a 'long memory.' Thus, it can be interpreted that gold price changes affect the future forecasts of gold price volatility for a longer period of time. The model also depicts that around 85% of the information associated with gold price volatility is derived from the previous days forecast.

The EGARCH (1, 1) model evaluates the existence of asymmetry in the volatility of spot gold returns by analyzing the effect of positive and negative shocks on gold price volatility by assuming the conditional variance is exponential. Table 3 below displays the results of the EGARCH (1, 1) model. (Annexure 4)

Table 3:- EGARCH (1, 1) Model

Dependent Variable: Spot returns in Gold				
Method: ML - ARCH (Marquardt) - Normal distribution				
LOG(GARCH) = C(2) + C(3)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(4) *RESID(-1)/@SQRT(GARCH(-1)) + C(5)*LOG(GARCH(-1))				
Mean Equation				
	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.000201	0.000179	-1.117164	0.2639
Variance Equation				
C(2)	-0.627749	0.098042	-6.402888	0.0000
C(3)	0.211709	0.018422	11.49228	0.0000
C(4)	-0.013012	0.011847	-1.098377	0.2720
C(5)	0.950414	0.009279	102.4274	0.0000

From the results of the above table it is understood that there is no leverage effect in the EGARCH model since the coefficient of the EGARCH model i.e. C (4) is negative at -0.013012 and insignificant meaning that there is no negative correlation between the past returns and future volatility of gold returns. It depicts that downward movement in gold daily return volatility is followed by higher volatility than an upward movement of the same magnitude.

The TARCH (1, 1) model also known as Threshold ARCH determines whether downward prices are treated separately from upward prices (Seiler, 2004). Table 4 below depicts the results of TARCH model. (Annexure 5)

Table 4:- TARCH (1, 1) Model

Dependent Variable: Spot returns in Gold				
Method: ML - ARCH (Marquardt) - Normal distribution				
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*RESID(-1)^2*(RESID(-1)<0) + C(5)*GARCH(-1)				
Mean Equation				
	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.000147	0.000208	-0.706625	0.4798
Variance Equation				
C	3.63E-06	7.83E-07	4.630197	0.0000
RESID(-1)^2	0.091081	0.012273	7.421131	0.0000
RESID(-1)^2*(RESID(-1)<0)	0.026033	0.016965	1.534558	0.1249
GARCH(-1)	0.853066	0.019140	44.56987	0.0000

From the above table it is clearly observed that the coefficient of TARCH term is positive (0.026033) and insignificant meaning that there is no leverage effect of TARCH model. This indicates that both positive and negative shocks have the same effect on future gold price volatility.

Robustness Checks:-

Finally, in order to verify the models are specified correctly, the diagnostic checking of all the models is being conducted. There are three conditions to be fulfilled by each of the models to be considered good or bad from the statistical point of view. They are (a) presence of no serial correlation, (b) presence of no ARCH effect and (c) normal distribution of residuals. Results of all the three tests for each of the models are being depicted in the following table. (Annexure 6 - 8).

Table 5:- Diagnostic Checking

Models	**Serial Correlation test**	**ARCH effect test**	**Normality test**
GARCH	Q stats > 0.05	Obs*R-squared 0.850233 Prob.Chi-Square(1) 0.3565	Jarque-Bera 415.8612 Probability 0.000000
EGARCH	Q stats > 0.05	Obs*R-squared 4.042965 Prob.Chi-Square(1) 0.0444	Jarque-Bera 531.4110 Probability 0.000000
TARCH	Q stats > 0.05	Obs*R-squared 1.526884 Prob.Chi-Square(1) 0.2166	Jarque-Bera 390.7251 Probability 0.000000

Table 5 above indicates that the probability value of the Q (36) statistic is not significant since the reported value is above .05 in case of all the three models. Thus, the null hypothesis of presence of no serial correlation in the residuals is accepted in GARCH, EGARCH and TARCH models. This indicates that the first condition of diagnostic checking is desirable. Secondly, the probability value of Chi-square is more than 5% in case of GARCH and TARCH model while in case of EGARCH model the same value is more than 1%. Thus the null hypothesis of presence of no ARCH effect in the residuals can not be rejected at 5% confidence level in case of GARCH and TARCH model and at 1% level of confidence in case of EGARCH model. Therefore, the second condition of diagnostic checking of presence of no ARCH effect is accepted which is desirable. Thirdly, the probability values of Jarque-Bera statistics of all the three models are found to be less than 1%. Thus, the null hypothesis of residuals are normally distributed is rejected at 1% confidence level for all the three models which is not desirable. However, many economists say that although the residuals are not normally distributed, the model can be accepted. Therefore, it can be concluded that all the ARCH family models are specified correctly in the study.

Conclusion:-

The present paper empirically analyzes time varying effects of price volatility using a family of ARCH models. Based on the theoretical and empirical literature that is reviewed in this study, the conditional variance hypothesis in the context of an emerging commodity market namely MCX has been investigated. The study examined the volatility in the gold spot price using daily data of closing price from MCX home page for a period of 5 and 1/2 years. It has examined the hypothesis by using different descriptive statistical tools namely mean, standard deviation, Jarque-Bera test etc and econometric tools like ARCH family models such as GARCH(1,1), EGARCH(1,1) and TARCH (1,1).

The results provide evidence that gold price changes affect the future forecasts of gold price volatility for a longer period of time. It means the volatility in the gold spot market exhibits the persistence of volatility. GARCH (1, 1) model also depicts that around 85% of the information associated with gold price volatility is derived from the previous days forecast. Further, the EGARCH model describes that there is no leverage effect meaning that there is no negative correlation between the past returns and future volatility of gold returns during the study period. Finally, the TARCH (1, 1) model indicates that both positive and negative shocks have the same effect on future gold price volatility. Various diagnostic checking tests like serial correlation test, ARCH effect test and normality test are also applied to verify the correctness of the used models. The outcomes indicate that all the ARCH family models are specified correctly in the study. Thus, the alternative hypothesis can be accepted that the future conditional variance in gold spot price is based on the past variances.

The present study subjects to certain inherent limitations. It is based on a limited period of 5 and ½ years i.e. from January, 2011 to June, 2016. Further, the study is meant for only gold and the spot price of it is collected from one commodity exchange i.e. MCX. The volatility in the gold spot market could impact the futures market. Therefore, the various players those who trade in gold should observe the futures markets in order to determine whether hedging gold price volatility is an appropriate risk management tool. Several other factors such as demand for gold and inflation would also be expected to have an impact on the spot price of gold in the country. These factors can be considered for further study in this area.

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Annexure-1:-
Augmented Dickey- Fuller Test:-

Null Hypothesis: GSP has a unit root				
Exogenous: Constant				
Lag Length: 0 (Automatic - based on SIC, maxlag=23)				
			t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic			-38.92274	0.0000
Test critical values:	1% level		-3.434552	
	5% level		-2.863283	

	10% level		-2.567746	
*MacKinnon (1996) one-sided p-values.				
Augmented Dickey-Fuller Test Equation				
Dependent Variable: D(GSP)				
Method: Least Squares				
Date: 07/26/16 Time: 12:30				
Sample (adjusted): 1/03/2011 6/29/2016				
Included observations: 1483 after adjustments				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
GSP(-1)	-1.011356	0.025984	-38.92274	0.0000
C	-0.000225	0.000234	-0.959921	0.3373
R-squared	0.505671	Mean dependent var		2.10E-06
Adjusted R-squared	0.505337	S.D. dependent var		0.012828
S.E. of regression	0.009022	Akaike info criterion		-6.576980
Sum squared resid	0.120545	Schwarz criterion		-6.569830
Log likelihood	4878.831	Hannan-Quinn criter.		-6.574315
F-statistic	1514.980	Durbin-Watson stat		1.999088
Prob(F-statistic)	0.000000			

Annexure 2:-
ARCH Model

Heteroskedasticity Test: ARCH				
F-statistic	113.0508	Prob. F(1,1481)		0.0000
Obs*R-squared	105.1751	Prob. Chi-Square(1)		0.0000
Test Equation:				
Dependent Variable: RESID^2				
Method: Least Squares				
Date: 07/26/16 Time: 12:36				
Sample (adjusted): 1/03/2011 6/29/2016				
Included observations: 1483 after adjustments				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	5.96E-05	6.05E-06	9.856340	0.0000
RESID^2(-1)	0.266308	0.025047	10.63254	0.0000
R-squared	0.070920	Mean dependent var		8.13E-05
Adjusted R-squared	0.070293	S.D. dependent var		0.000228
S.E. of regression	0.000219	Akaike info criterion		-14.00949
Sum squared resid	7.13E-05	Schwarz criterion		-14.00234
Log likelihood	10390.03	Hannan-Quinn criter.		-14.00682
F-statistic	113.0508	Durbin-Watson stat		2.052522
Prob(F-statistic)	0.000000			

Annexure-3:-
GARCH Model

Dependent Variable: GSP				
Method: ML - ARCH (Marquardt) - Normal distribution				
Date: 07/26/16 Time: 12:39				
Sample: 1/01/2011 6/29/2016				
Included observations: 1484				
Convergence achieved after 14 iterations				
Presample variance: backcast (parameter = 0.7)				
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)				
Variable	Coefficient	Std. Error	z-Statistic	Prob.

C	-0.000104	0.000202	-0.517331	0.6049
	Variance Equation			
C	3.67E-06	7.13E-07	5.143865	0.0000
RESID(-1)^2	0.106173	0.012272	8.651586	0.0000
GARCH(-1)	0.850975	0.017928	47.46546	0.0000
R-squared	-0.000173	Mean dependent var		-0.000223
Adjusted R-squared	-0.000173	S.D. dependent var		0.009016
S.E. of regression	0.009017	Akaike info criterion		-6.744651
Sum squared resid	0.120582	Schwarz criterion		-6.730358
Log likelihood	5008.531	Hannan-Quinn criter.		-6.739324
Durbin-Watson stat	2.022317			

Annexure-4:-
EGARCH Model

Dependent Variable: GSP				
Method: ML - ARCH (Marquardt) - Normal distribution				
Date: 07/26/16 Time: 12:41				
Sample: 1/01/2011 6/29/2016				
Included observations: 1484				
Convergence achieved after 21 iterations				
Presample variance: backcast (parameter = 0.7)				
LOG(GARCH) = C(2) + C(3)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(4)				
*RESID(-1)/@SQRT(GARCH(-1)) + C(5)*LOG(GARCH(-1))				
Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.000201	0.000179	-1.117164	0.2639
	Variance Equation			
C(2)	-0.627749	0.098042	-6.402888	0.0000
C(3)	0.211709	0.018422	11.49228	0.0000
C(4)	-0.013012	0.011847	-1.098377	0.2720
C(5)	0.950414	0.009279	102.4274	0.0000
R-squared	-0.000006	Mean dependent var		-0.000223
Adjusted R-squared	-0.000006	S.D. dependent var		0.009016
S.E. of regression	0.009016	Akaike info criterion		-6.738849
Sum squared resid	0.120562	Schwarz criterion		-6.720983
Log likelihood	5005.226	Hannan-Quinn criter.		-6.732189
Durbin-Watson stat	2.022654			

Annexure-5:-
TARCH Model

Dependent Variable: GSP		
Method: ML - ARCH (Marquardt) - Normal distribution		
Date: 07/26/16 Time: 12:44		
Sample: 1/01/2011 6/29/2016		
Included observations: 1484		
Convergence achieved after 15 iterations		
Presample variance: backcast (parameter = 0.7)		
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*RESID(-1)^2*(RESID(-1)<0) +		
C(5)*GARCH(-1)		

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.000147	0.000208	-0.706625	0.4798
	Variance Equation			
C	3.63E-06	7.83E-07	4.630197	0.0000
RESID(-1)^2	0.091081	0.012273	7.421131	0.0000
RESID(-1)^2*(RESID(-1)<0)	0.026033	0.016965	1.534558	0.1249
GARCH(-1)	0.853066	0.019140	44.56987	0.0000
R-squared	-0.000071	Mean dependent var		-0.000223
Adjusted R-squared	-0.000071	S.D. dependent var		0.009016
S.E. of regression	0.009017	Akaike info criterion		-6.744255
Sum squared resid	0.120570	Schwarz criterion		-6.726389
Log likelihood	5009.237	Hannan-Quinn criter.		-6.737596
Durbin-Watson stat	2.022523			

Annexure 6:-

	Q statistics of GARCH model					Q statistics of EGARCH model					Q statistics of TARCH model			
	AC	PAC	Q-Stat	Prob*		AC	PAC	Q-Stat	Prob*		AC	PAC	Q-Stat	Prob*
1	0.016	0.016	0.4000	0.527	1	0.013	0.013	0.2558	0.613	1	0.016	0.016	0.3878	0.533
2	0.061	0.061	5.9145	0.052	2	0.058	0.058	5.3421	0.069	2	0.061	0.061	6.0061	0.050
3	0.004	0.002	5.9392	0.115	3	-0.002	-0.004	5.3500	0.148	3	0.005	0.003	6.0384	0.110
4	0.051	0.047	9.8008	0.044	4	0.048	0.045	8.8358	0.065	4	0.052	0.048	10.010	0.040
5	0.025	0.024	10.768	0.056	5	0.020	0.019	9.4309	0.093	5	0.026	0.024	11.039	051
6	0.044	0.038	13.701	0.033	6	0.044	0.038	12.320	0.055	6	0.044	0.038	13.920	0.031
7	0.001	-0.003	13.703	0.057	7	0.000	-0.003	12.320	0.091	7	-0.000	-0.004	13.920	0.053
8	0.004	-0.003	13.724	0.089	8	0.000	-0.006	12.320	0.137	8	0.002	-0.005	13.927	0.084
9	0.036	0.034	15.704	0.073	9	0.038	0.037	14.467	0.107	9	0.036	0.034	15.826	0.071
10	-0.006	-0.011	15.753	0.107	10	-0.005	-0.009	14.499	0.151	10	-0.005	-0.011	15.868	0.103
11	0.011	0.006	15.951	0.143	11	0.010	0.004	14.644	0.199	11	0.012	0.006	16.073	0.138
12	-0.022	-0.024	16.700	0.161	12	-0.024	-0.024	15.488	0.216	12	-0.022	-0.023	16.825	0.156
13	0.008	0.005	16.800	0.209	13	0.007	0.004	15.563	0.274	13	0.009	0.005	16.934	0.202
14	-0.022	-0.021	17.547	0.228	14	-0.020	-0.018	16.185	0.302	14	-0.021	-0.020	17.605	0.225
15	0.002	-0.00	17.551	0.287	15	-0.00	-0.00	16.204	0.369	15	0.002	-0.00	17.610	0.284

		2				4	8					2		
16	-0.015	-0.010	17.897	0.330	16	-0.015	-0.010	16.540	0.416	16	-0.016	-0.011	17.981	0.325
17	-0.023	-0.023	18.708	0.346	17	-0.021	-0.020	17.202	0.441	17	-0.023	-0.023	18.775	0.342
18	-0.012	-0.007	18.916	0.397	18	-0.013	-0.009	17.466	0.491	18	-0.012	-0.008	18.988	0.393
19	-0.022	-0.018	19.643	0.416	19	-0.019	-0.016	18.011	0.522	19	-0.022	-0.018	19.700	0.413
20	0.009	0.013	19.768	0.472	20	0.010	0.014	18.176	0.576	20	0.008	0.012	19.803	0.470
21	-0.052	-0.046	23.872	0.299	21	-0.052	-0.047	22.317	0.381	21	-0.053	-0.048	24.080	0.289
22	-0.002	0.000	23.880	0.354	22	-0.006	-0.005	22.380	0.437	22	-0.003	-0.001	24.097	0.342
23	-0.013	-0.001	24.132	0.397	23	-0.014	-0.003	22.677	0.480	23	-0.014	-0.003	24.395	0.382
24	-0.002	-0.002	24.140	0.454	24	0.001	0.001	22.677	0.539	24	-0.004	-0.004	24.420	0.438
25	-0.033	-0.025	25.746	0.421	25	-0.034	-0.027	24.383	0.497	25	-0.032	-0.024	25.950	0.410
26	-0.036	-0.034	27.699	0.373	26	-0.034	-0.032	26.081	0.459	26	-0.036	-0.034	27.924	0.362
27	-0.023	-0.014	28.532	0.384	27	-0.023	-0.014	26.914	0.468	27	-0.024	-0.014	28.764	0.372
28	-0.038	-0.033	30.681	0.331	28	-0.035	-0.031	28.745	0.426	28	-0.038	-0.033	30.942	0.320
29	-0.008	-0.003	30.776	0.376	29	-0.009	-0.005	28.856	0.473	29	-0.008	-0.004	31.049	0.363
30	0.005	0.017	30.815	0.425	30	0.006	0.017	28.919	0.522	30	0.005	0.017	31.091	0.411
31	0.024	0.028	31.704	0.431	31	0.026	0.030	29.958	0.519	31	0.025	0.029	32.039	0.415
32	-0.035	-0.030	33.616	0.389	32	-0.037	-0.032	32.009	0.466	32	-0.035	-0.029	33.866	0.378
33	0.031	0.029	35.030	0.372	33	0.035	0.032	33.821	0.428	33	0.032	0.030	35.384	0.356
34	-0.002	0.005	35.040	0.419	34	-0.002	0.005	33.828	0.476	34	-0.001	0.006	35.388	0.403
3	-	-	35.43	0.448	3	-	-	34.38	0.498	3	-	-	35.76	0.432

5	0.016	0.024	4		5	0.019	0.027	4		5	0.016	0.024	9	
36	-0.022	-0.020	36.143	0.462	36	-0.021	-0.020	35.081	0.512	36	-0.021	-0.020	36.435	0.448

Annexure 7:-

ARCH Effect Test (GARCH Model):-

Heteroskedasticity Test: ARCH			
F-statistic	0.849574	Prob. F(1,1481)	0.3568
Obs*R-squared	0.850233	Prob. Chi-Square(1)	0.3565

ARCH Effect Test (EGARCH Model):-

Heteroskedasticity Test: ARCH			
F-statistic	4.048550	Prob. F(1,1481)	0.0444
Obs*R-squared	4.042965	Prob. Chi-Square(1)	0.0444

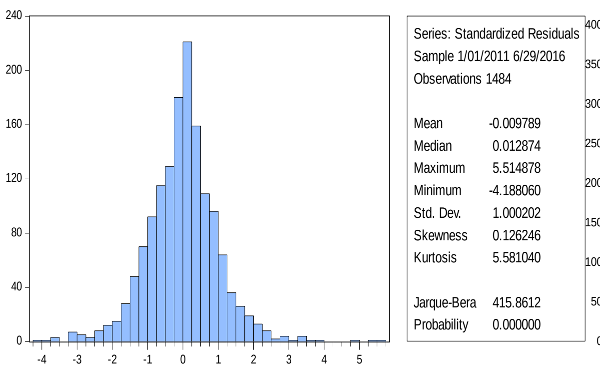
ARCH Effect Test (TARCH Model)

Heteroskedasticity Test: ARCH			
F-statistic	1.526397	Prob. F(1,1481)	0.2168
Obs*R-squared	1.526884	Prob. Chi-Square(1)	0.2166

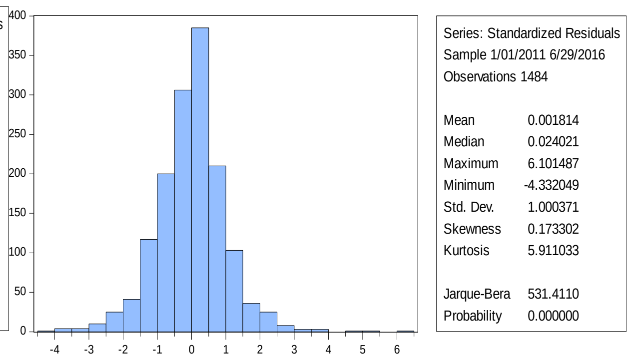
Annexure 8:-

Normality Test:-

GARCH



EGARCH



TARCH