Modelling Volatility Clustering and Asymmetry : A Study of Indian Index Futures Markets

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Abstract

The main objective of this paper was to study volatility clustering and asymmetrical features of the Indian index futures markets using the most commonly used symmetrical and asymmetrical generalized autoregressive conditional heteroskedasticity models such as traditional GARCH and threshold GARCH (TGARCH), respectively. To achieve the objectives of the study, NIFTY futures index - FUTIDX and MCX futures index - MCXCOMDEX was used as a proxy to the Indian stock and commodity futures market, respectively. The daily data for selected indices were collected for a period of 12 years from May 13, 2006 to June 13, 2018 from the official websites of the respective exchanges. The results of the study indicated that though conditional volatility was present in both of the selected futures markets, but threshold effect as well as leverage effect was present in the Indian stock futures market only. Therefore, we concluded that negative and positive news did not have a symmetrical impact on the volatility of stock futures market returns, and moreover, bad news created more volatility in the Indian stock futures market as compared to good news.

Keywords: **asymmetric volatility, GARCH, TGARCH, commodity futures (MCXCOMDEX), stock futures (FUTIDX), leverage effects**

JEL Classification: C58, G1, G13

Paper Submission Date : July 18, 2018 ; Paper sent back for Revision : February 7, 2019 ; Paper Acceptance Date : February 18, 2019

Derivatives are those financial instruments that have no independent value, but derive their value from underlying financial assets' performance such as index, currency, stock, commodity (gold, silver, wheat, and so on), bonds, interest rate, etc. According to Section 2 of amended Securities Contracts (Regulation) Act, 1956 (SCRA), a "derivative" includes : (a) a security derived from a debt instrument, share, loan, whether secured or unsecured, risk instrument, or contract for differences or any other form of security; (b) a contract which derives its value from the prices, or index of prices, of underlying securities.

Derivatives are used for various purposes such as hedging, that is, to indemnify against assets' risk or for speculation purpose with an objective of getting substantial returns or it can be used by arbitrageurs to earn extra returns due to difference in the prices of asset in different markets. Further, it can also be used as an important asset class for portfolio diversification with an objective to minimize risk. There are various types of derivatives such as : exchange traded (futures and options) and over-the-counter (forwards and swaps). There are two types of future contracts such as stock futures and index futures. This paper is basically focusing on the asymmetrical volatility behaviour of two future index derivatives such as stock futures index and commodity futures index.

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DOI : 10.17010/ijf/2019/v13i3/142269

Review of Literature

Abounoori and Nademi (2011) used modified GARCH model, that is, GJR models with both Gaussian and fat-tailed distribution to study the asymmetric effect of news on volatility of Tehran Stock Exchange (TSE) for the period of approximately 13 years ranging from September 29, 2007 to September 9, 2010. The results of their study confirmed the presence of leverage effect in the selected stock exchange, which means that bad news had a larger impact on volatility of TSE as compared to good news.

Amudha and Muthukamu (2018) attempted to examine symmetric and asymmetric volatility among NSE listed 13 auto sectoral stocks spanning the period from April 2003 to September 2015 using GARCH (1, 1), EGARCH (1, 1), and TGARCH (1, 1) models. Their study confirmed the presence of volatility persistence and leverage effect in the Indian stock market. Furthermore, they added that EGARCH (1, 1) model proved to be the best fitted model to capture the leverage effect.

Mall, Pradhan, and Mishra (2011) studied the asymmetric nature of India's stock index futures market's volatility by using daily closing prices of near month NSE index futures contract (FUTDIX) from June 2000 to May 2011 with the help of GARCH class models such as GARCH (1, 1), EGARCH (1, 1), and TGARCH (1, 1). The results of their study concluded that bad news increased the volatility of India's stock index futures market substantially.

Singh and Ahmad (2011) estimated the performance of GARCH- family models under three different error distributions (Gaussian, Student - *t*, and GED) in estimating stock market volatility of National Stock Exchange of India index (S&P CNX Nifty) for the period of June 1, 2001 to December 31, 2008. Their empirical results ensured the presence of the conditional variance, leverage effect, and significant persistence in the long run component. Further, on the basis of log likelihood, Jarque - Bera statistics, residuals kurtosis & skewness, and forecasting performance, they reported that T-GARCH, and P-GARCH with Gaussian distribution were best to capture the characteristics of Nifty returns.

Gil - Alana and Tripathy (2014) used the GARCH class of models such as GARCH, TGARCH, and EGARCH to study the volatility persistence and leverage effect across 12 non-ferrous metals (aluminium, tin, nickel, lead, zinc, and copper) series including both futures and spot from January 1, 2009 to June 30, 2012. Their results indicated that EGARCH captured leverage effect in 10 series; however, TGARCH captured the leverage effect in seven series only.

Srikanth (2014) ensured the presence of leverage effect in the Indian stock market by applying two asymmetric GARCH models : GJR - GARCH model and Power GARCH (PGARCH) model on daily wise returns of BSE Sensex for the period from July 1, 1997 to March 30, 2013.

Mattack and Saha (2016) applied ARMA - GARCH (*p, q*) model on adjusted closing prices of 83 stocks listed on NSE for 17 years from January 1998 to December 2014 to examine whether the introduction of derivatives (options and futures) led to stock market instability. They concluded that most of selected stocks' volatility decreased with the listing of equity derivatives.

Musunuru (2016) investigated the existence of conditional volatility and news asymmetry in soybeans futures returns (one of the actively traded agricultural commodities on the Chicago Board of Trade) by applying symmetrical (GARCH) and three asymmetrical GARCH models (EGARCH, TGARCH, and APARCH) using quasi maximum likelihood estimation under three distributions such as normal, student's *t*, and GED for the period of 20 years ranging from January 4, 1993 to May 31, 2013. Their results confirmed the presence of conditional volatility but absence of asymmetric leverage effect in the return series of the selected commodity which indicated that more volatility was caused by positive news rather than negative news. Further, on the basis of diagnostic tests, they found that APARCH (1, 3) model with *t* - distribution performed best in capturing the dynamic behaviour of the soybean return series.

Al - Najjar (2016) examined the volatility features such as volatility clustering, leptokurtosis, and leverage effect of Amman Stock Exchange General Index (ASEI) used as a surrogate index for Jordan's capital market for the period from January 1, 2005 to December 31, 2014 using symmetric GARCH and asymmetric GARCH (Exponential GARCH) models. The results of their study ensured the existence of volatility clustering and leptokurtic features of sample stock index, however, the output of EGARCH didn't confirm the existence of leverage effect in ASEI.

Varughese and Mathew (2017) examined the existence of volatility clustering, leverage effect, and the contribution of foreign portfolio investment (FPIs) of Indian stock market return volatility by applying both symmetric and asymmetric GARCH family models such as GARCH (1, 1), E-GARCH, and TARCH models on daily NSE returns for the period of 12 years ranging from April 1, 2003 to March 31, 2015. Their study confirmed the existence of volatility clustering and asymmetric volatility in the Indian stock market. Further, they also concluded that FPIs had a significant negative impact on the stock market's volatility, that is, FPIs reduced the volatility of the Indian stock market.

Natchimuthu and Prakasam (2018) applied various GARCH family models such as GARCH, TGARCH, EGARCH, and PGARCH on NSE broad as well as sectoral indices over the period of 18 years to investigate the presence of conditional volatility, leverage effect, and long term memory feature in the Indian capital market. Their study ensured the presence of all the above mentioned features for which the Indian capital market was tested. Further, they also concluded that PGARCH model performed better in comparison to the above mentioned other asymmetrical models on the basis of AIC and log likelihood parameters.

It is evident from earlier studies discussed above that most of the studies are related to examining the presence of volatility clustering and leverage effect in the Indian capital market, but the studies that focused on identifying such volatility features of the Indian futures market are negligible. Therefore, the current study has been carried out to fill this research gap.

Research Objectives

(1) To examine the presence of volatility clustering in the Indian stock and commodity futures markets.

(2) To examine the existence of asymmetric volatility in the Indian stock and commodity futures markets.

Research Methodology

(1) Data: This study is secondary data based. The FUTIDX (Nifty futures index) and MCXCOMDEX (MCX composite commodity index) are used as proxy to the Indian stock futures and commodity market, respectively. The daily near month closing future prices of both indices were collected from the official website of NSE (National Stock Exchange of India Ltd.) and MCX (Multi Commodity Exchange Limited), respectively. The sample period selected for the purpose of study is from May 13, 2006 to June 13, 2018 on the basis of availability of data on the websites of both the exchanges.

(2) Statistical Tests : Before estimating ARCH/GARCH models, it in mandatory to check residuals for unit root and ARCH effect.

(I) Stationarity : The basic assumption of ARCH models is that the data should be stationary. The daily closing values of both selected indices are having unit root. Therefore, first we converted the price series (non stationary series) of both indices such as FUTIDX and MCXCOMDEX into return series (R_t - stationary series) with the help of equation (1) given below. These return series are named as RFUTIDX and RMCXCOMDEX.

$$R_t = \log P_t - \log P_{t-1} \qquad \text{-----(1)}$$

In order of check the stationarity of return series, graphs and Augmented Dickey - Fuller (ADF), parametric unit root test have been used. The return series is said to be stationary if the ADF test rejects the null hypothesis of unit root ($\rho = 1$) in the return series.

(ii) ARCH Effect : Once the series has become stationary, the next step is to check whether the residuals have ARCH effects or not. The presence of ARCH effect in the residuals ensure the presence of volatility clustering in underlying indices and provide the basis for applying symmetrical as well as asymmetrical GARCH models.

(iii) GARCH Model : The generalized autoregressive conditional heteroskedasticity (GARCH) model is a superior model than the ARCH model because it is a long memory process which uses all the past squared residuals rather than the most recent q squared residuals to estimate the current conditional variance. The output of the GARCH model consists of two equations :

$$\text{Mean Equation: } Y_t = \alpha + \beta Y_{t-1} + u_t \qquad \text{-----(2)}$$

where, α is constant,

βY_{t-1} is the coefficient of autoregressive term,

$u_t \sim N(0, \sigma^2)$ and σ^2 is time variant and dependent on the past history.

Conditional Variance Equation : u_t in equation 2 is the error term which is not a white noise because its variance (σ^2) is not constant over time. Therefore, we need to decompose u_t in two parts : one which is explainable (h_t) and one which is complete white noise (ε_t).

$$u_t = \varepsilon_t \sqrt{h_t} \; ; \; h_t = \sigma^2 \qquad \text{-----(3)}$$

where $\varepsilon_t \sim N(0, 1)$, that is, ε_t is white noise,
h_t is the systematic variance, which is time variant.

Thus, GARCH model or conditional variance equation can be written as :

$$h_t = \gamma_0 + \gamma_1 u^2_{t-1} + \delta_1 h_{t-1} \qquad \text{-----(4)}$$

where, γ_0 is constant.
γ_1 is the coefficient of ARCH term which measures the extent to which the preceding information impacts the conditional volatility of financial market's returns, that is, whether volatility in the sample series is sensitive to past market information or not.
δ_1 is the coefficient of GARCH term which measures whether volatility in the sample series is persistent or not.
Thus, h_t is dependent on two things: Firstly, past values of the error which is captured by u^2_{t-1} and secondly, on past values of itself which is captured by h_{t-1}.

(iv) Asymmetric GARCH Model : Threshold Generalized Autoregressive Conditional Heteroskedasticity (Threshold GARCH or TGARCH) model is one of an asymmetric GARCH model that is used in this paper instead of standard GARCH model because the latter is based on an assumption that positive and negative error terms have a symmetric (same) effect on the volatility as residuals are squared term. But in reality, financial markets respond differently in response to good and bad news, that is, reaction of volatility to the sign of the shocks is asymmetrical. If the bad news creates more volatility in index returns than good news, then it is known as leverage effect. TGARCH model was introduced by Zakoian (1994). It is a non - linear ARCH model that does modelling of conditional variance rather than conditional standard deviation.

A TGARCH (1, 1) is given by :

$$h_t = \gamma_0 + \gamma_1 u^2_{t-1} + \lambda_1 u^2_{t-1} d_{t-1} + \delta_1 h_{t-1} \qquad \text{---- (5)}$$

where, $d_{t-1} = 1$; if $u_{t-1} < 0 \rightarrow$ Negative Shock

$= 0$; if $u_{t-1} \geq 0 \rightarrow$ Positive Shock

That is, depending on whether u_{t-1} is above or below the threshold value of zero. The u^2_{t-1} has different effects on the conditional variance (h_t). When the value of u_{t-1} is positive (i.e. $u_{t-1} \geq 0$), then the effect of u_{t-1} on h_t is λ_1, however, if the value of u_{t-1} is negative (i.e. $u_{t-1} < 0$), then the effect of u_{t-1} on h_t is ($\gamma_1 + \lambda_1$). So, if λ_1 (the coefficient of d_{t-1}) is greater than zero, or positive, and statistically significant too, then it means bad news creating more volatility in contrast to good news and vice versa.

Empirical Analysis and Results

(1) Descriptive Statistics : Descriptive statistics of both the return variables are outlined in the Table 1, which indicates that the stock futures market has higher returns as well as higher volatility as compared to commodity futures market. Thus, it is evident from this table that one can fetch higher returns by investing in higher volatile security. Both the return series are negatively skewed and have kurtosis greater than 3, which means that the distributions are leptokurtic.

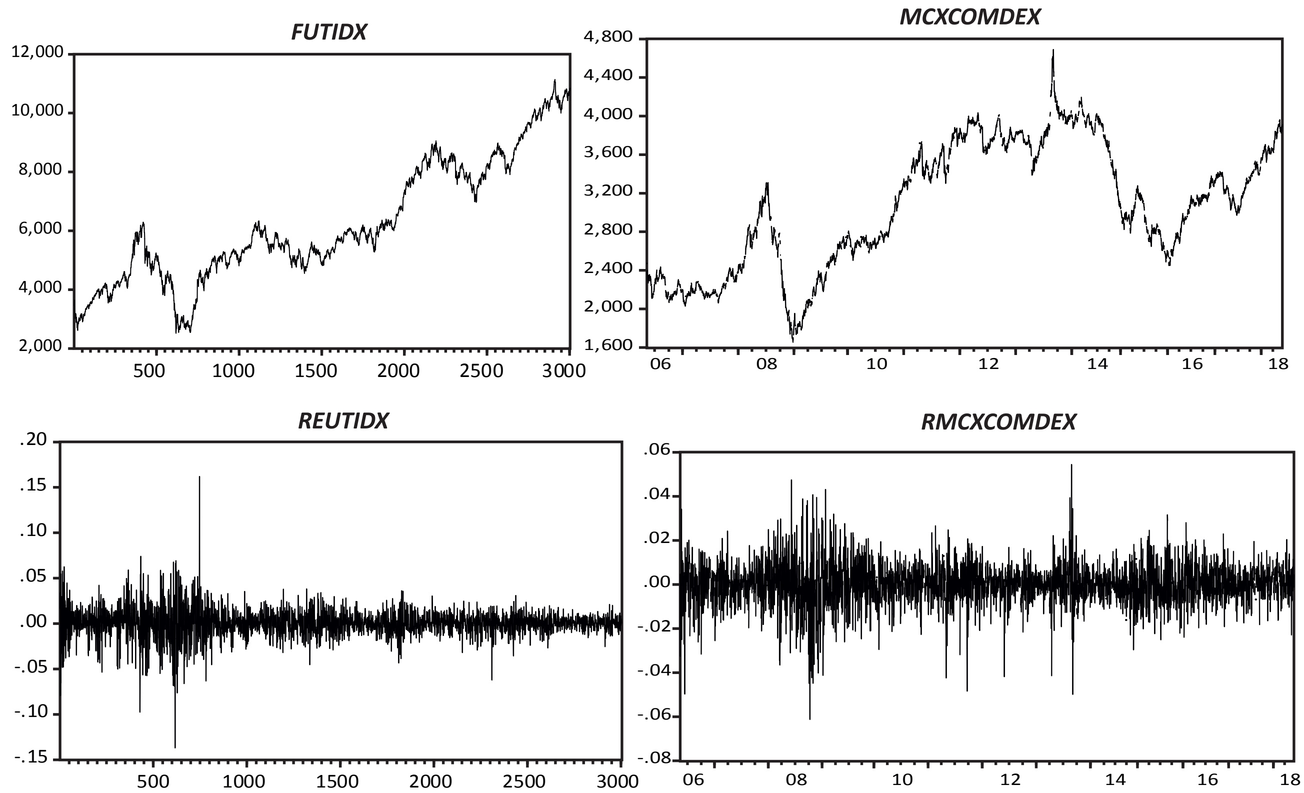
The *p* - value of Jarque - Bera statistics is significant at the 5% level of significance, which rejects the null

Table 1. Descriptive Statistics Results

	RFUTIDX	*RMCXCOMDEX*
Mean	**0.000380**	0.000048
Median	0.000601	0.000421
Maximum	0.161947	0.054383
Minimum	-0.136774	-0.250166
Std. Dev.	**0.015271**	0.010273
Skewness	-0.108512	**-4.388966**
Kurtosis	12.768770	**105.625600**
Jarque-Bera	11942.45	1541408
Probability	0.000000*	0.000000*
Sum	1.141829	0.167077
Sum Sq. Dev.	0.699817	0.367922
Observations	3002	3487

Note. * Significant at 5% level

Figure 1. Graphical Presentation of Price and Return Series



hypothesis that the distributions of both the return series are normal. Though the time period selected for collecting index value of both financial markets is same, but the number of observations in commodity market (3487) is more as compared to stock market (3002) because of non - synchronous trading days.

(2) Stationarity : Initially, the stationarity of time series has been checked with the help of graphs and then by applying parametric unit root test.

(i) Graphical Presentation : It is evident from the Figure 1 that price series of both selected indices - FUTDIX and MCXCOMDEX are not stationary at level because neither their mean nor their variance is constant over time. Further, Nifty futures price series have trend element in contrast to commodity price index. However, both the return series - RFUTDIX and RMCXCOMDEX are stationary at level because their mean and unconditional variance is constant for the study period. Also, there is presence of conditional variance which can be captured by ARCH advanced models in the following sections.

(ii) Unit Root Tests : In this section of the paper, ADF test has been used among various unit root tests to check the robustness of the graph results.

It is clear from the Table 2 that price series of both indices have unit root because p-values corresponding to t - statistics are not significant at the 5% level of significance. However, in case of both the return series, p-values corresponding to t - statistics are less than 0.05. Thus, both the return series are stationary at level, that is, not having unit root. Therefore, return series of both indices will be used for further analysis.

Table 2. ADF Unit Root Test Results

Series	Variables	Trend & Intercept or Intercept only	ADF Test		Critical Value	Stationary
			***t* - statistics**	**prob.**	**at 5%**	
Price Series	*FUTIDX*	trend & intercept#	-2.3150	0.4251	-3.4113	No
	MCXCOMDEX	intercept	-1.0958	0.7197	-2.8217	
Return Series	*RFUTIDX*	intercept	-53.8266	0.0001*	-2.8623	Yes
	RMCXCOMDEX	intercept	-57.9333	0.0001*	-2.8622	

Note. * Significant at 5% level

only this particular series having significant trend at level.

(3) Volatility Clustering in the Indian Stock Market and Commodity Futures Returns

(I) Residual Distribution : Volatility clustering is a normal feature of stock prices (Al - Najjar, 2016 ; Varughese & Mathew, 2017). To ensure the presence of this feature in stock and commodity futures prices, we developed regression equation for each return series and their residual distributions are plotted in the Figure 2. It is evident from the Figure 2 that there is presence of volatility clustering in the residuals of both the return series. In other words, we can say that periods of small volatility are followed by small ones and periods of large volatility are followed by large ones of either sign for a long period.

(ii) ARCH - LM Test : Before proceeding for various volatility models and to statistically confirm the presence of volatility clustering, first we need to check the existence of the ARCH effect in the residuals of mean equation of both return series with the help of the ARCH - LM test. The Table 3 shows the results for the same. It is observed that in case of both return series, the probability value of *F*-statistics is less than 5%. This test ensures that variability in residuals is not constant over the sample period, that is, return series of both the selected indices exhibit time-varying volatility clustering, that is, periods of high volatility are followed by periods of low volatility.

Figure 2. Residual Distribution

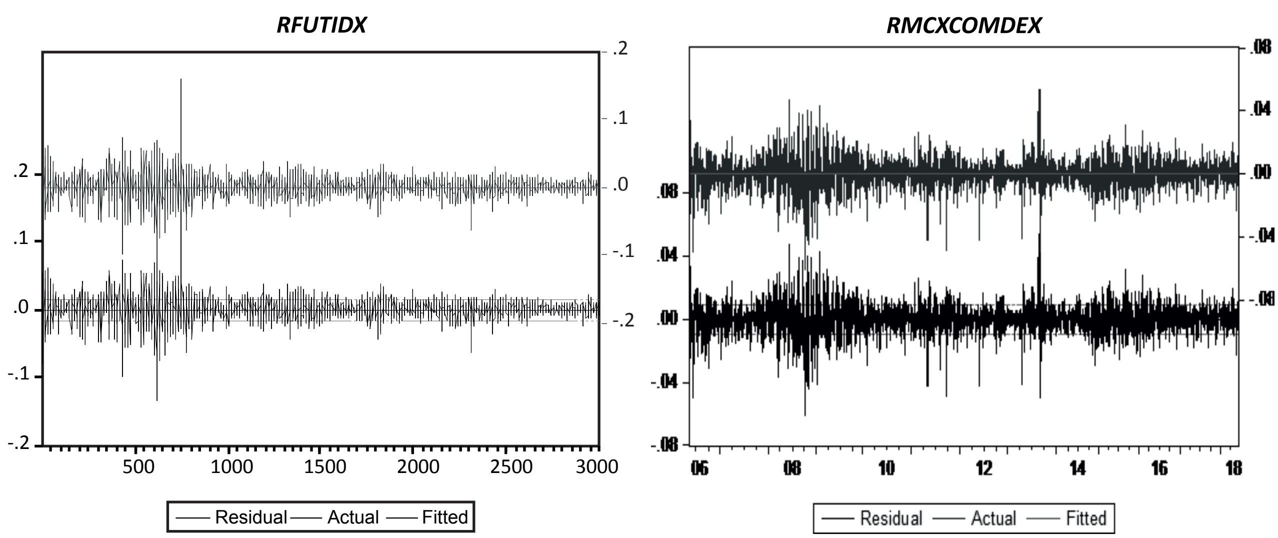


Table 3. Heteroskedasticity Test : ARCH

(i) For *RFUTIDX*			
F - statistics	68.12481	Prob. *F* (1,2999)	0.0000*
Observed *R*-squared	66.65610	Prob. Chi-Square(1)	0.0000
(ii) For *RMCXCOMDEX*			
F-statistics	94.87980	Prob. *F* (1,3484)	0.0000*
Observed *R*-squared	92.41746	Prob. Chi-Square(1)	0.0000

Note. *Significant at 5% level

(iii) GARCH (*p, q*) Model : The existence of heteroskedasticity (ARCH effect) in the residuals of both return series is ensured by ARCH-LM test, therefore, we can proceed further for applying the GARCH family models. This model is considered to be superior as compared to traditional regression model for volatility modelling because it is not based on assumption of constant variance like the latter one. In GARCH (*p, q*) model, *p* represents the order of GARCH term and *q* represents the order of ARCH term. In this section, conditional variances are estimated from the GARCH (1, 1) model because this model is equivalent to infinite order ARCH model with geometrically

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

(I)		**For *FUTIDX***		
GARCH = *C*(3) + *C*(4)*RESID(-1)^2 + *C*(5)*GARCH(-1)				
Variable	**Coefficient**	**Std. Error**	***z* - Statistic**	**Prob.**
C	0.000678	0.000179	3.782519	0.0002
RFUTIDX(-1)	0.032988	0.020421	1.615396	0.1062
		Variance Equation		
C	1.44E-06	2.50E-07	5.745080	0.0000
RESID(-1)^2	0.078718	0.006176	12.74525	0.0000*
GARCH(-1)	0.915121	0.006191	147.8209	0.0000*
Schwarz criterion	-5.979054	Akaike info criterion		-5.989062
ii)		**For *RMCXCOMDEX***		
GARCH = *C*(4) + *C*(5)*RESID(-1)^2 + *C*(6)*GARCH(-1)				
Variable	**Coefficient**	**Std. Error**	***z* - Statistic**	**Prob.**
C	0.000187	0.000135	1.382046	0.1670
RMCXCOMDEX (-1)	0.032552	0.017285	1.883223	0.0597**
RMCXCOMDEX (-2)	0.041887	0.017018	2.461313	0.0138*
		Variance Equation		
C	1.10E-06	1.50E-07	7.308473	0.0000
RESID(-1)^2	0.053876	0.004123	13.06736	0.0000*
GARCH(-1)	0.932677	0.005197	179.4615	0.0000*
Schwarz criterion	-6.682126	Akaike info criterion	-6.692725	

Note. *Significant at 5% level and ** Significant at 10% level declining coefficients. The parameters estimated for GARCH (1, 1) model for both sample indices are presented in Table 4.

It is evident from the Table 4 that for RFUTIDX, AR(1) - GARCH(1,1) model is recognized to be a good model, however, for RMCXCOMDEX, the good model is AR(2) - GARCH(1,1). The ARCH and GARCH coefficients of both return series are positive and significant at the 5% level of significance (p - values 0.05) . This indicates that the present period of volatility of RFUTIDX and RMCXCOMDEX is significantly affected by the precedent period's volatility.

Further, the total of ARCH (lagged squared residual terms : RESID(-1)^2) and GARCH (lagged h_t term) coefficient in each return series is close to 1 and also the value of GARCH coefficient is much larger than the coefficient of the ARCH term. Thus, we can conclude that volatility shocks in both the financial markets are quite persistent and take some time to die out. However, shocks in the commodity futures market (0.932677) are more persistent than NIFTY futures market's shocks (0.915121).

(4) Asymmetrical Volatility in the Indian Stock Market and Commodity Futures Returns

(i) TGARCH (*p, q*) Model : One of the biggest limitations of standard ARCH/GARCH models is that they consider only the magnitude of returns ; however, information regarding return's direction is totally ignored. The standard ARCH/GARCH models are based on the assumption that good and bad news have a symmetrical effect on market returns ; however, in reality, this assumption does not hold true. Thus, TGARCH (*p, q*) model is employed to capture the volatility of asymmetric nature in return series of both indices. In TGARCH (*p, q*) model, *p* represents the order of threshold term and *q* represents the order of GARCH term. The results of TGARCH (1, 1) model for both the return series are presented in the Table 5.

➯ **For RFUTIDX :** It is clear from the first part of Table 5 that the value of TGARCH coefficient (RESID (-1)^2*(RESID(-1)<0)) for RFUTIDX is positive and significant at the 5% level of significance, which implies that bad news creates more volatility as compared to good news in NIFTY futures market. Thus, it confirms the presence of leverage effect. Further, in case of this return series, the TGARCH model is considered to be a superior model than the GARCH model fitted earlier because AIC as well as SC values for TGARCH (1, 1) model is less than its corresponding value for GARCH (1, 1) model.

➯ **For RMCXCOMDEX :** It is clear from the second part of Table 5 that the value of TGARCH coefficient for RMCXCOMDEX (0.7567) is not statistically significant even at the 10% level of significance. This implies that there is no threshold effect in the return series of MCXCOMDEX index, which is taken as proxy for commodity futures market. Thus, we can conclude that the impact of positive and negative news on commodity futures market index volatility is indifferent or same. It means that every price change responds symmetrically to the good and bad news in the commodity market. As a result, the standard GARCH model is considered to be superior than the TGARCH model for commodity futures market because AIC and SC values for GARCH (1, 1) model are lower as compared to their corresponding values for TGARCH (1, 1) model.

(ii) Residual Diagnostics : Though in the above section, on the basis of information criterion, we have concluded that for stock futures return series, the TGARCH (1,1) model is considered to be a superior model than GARCH (1,1), however, for commodity futures return series, it is the other way around. Further, in this section, we carry out residual diagnostics of selected models for both the financial markets to ensure that the models are adequate enough, that is, do not suffer from the following problems.

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

(i)	For *RFUTIDX*			
GARCH = *C*(3) + *C*(4)*RESID(-1)^2 + *C*(5)*RESID(-1)^2*(RESID(-1)<0) + *C*(6)*GARCH(-1)				
Variable	**Coefficient**	**Std. Error**	**z-Statistic**	**Prob.**
C	0.000408	0.000184	2.216875	0.0266
RFUTIDX(-1)	0.042264	0.020563	2.055326	0.0398*
	Variance Equation			
C	1.93E-06	2.48E-07	7.767521	0.0000
RESID(-1)^2	0.033264	0.005555	5.988110	0.0000*
RESID(-1)^2*(RESID(-1)<0)	0.095890	0.009057	10.58727	0.0000*
GARCH(-1)	0.909271	0.006244	145.6327	0.0000*
Schwarz criterion	-5.992307	Akaike info criterion	-6.004317	
(ii)	**For *RMCXCOMDEX***			
GARCH = *C*(4) + *C*(5)*RESID(-1)^2 + *C*(6)*RESID(-1)^2*(RESID(-1)<0) + *C*(7)*GARCH(-1)				
Variable	**Coefficient**	**Std. Error**	***z* - Statistic**	**Prob.**
C	0.000192	0.000137	1.396830	0.1625
RMCXCOMDEX(-1)	0.032703	0.017334	1.886666	0.0592**
RMCXCOMDEX(-2)	0.041942	0.017302	2.424139	0.0153*
	Variance Equation			
C	1.10E-06	1.56E-07	7.031346	0.0000
RESID(-1)^2	0.054938	0.005966	9.207954	0.0000*
RESID(-1)^2*(RESID(-1)<0)	-0.002072	0.006688	-0.309867	0.7567
GARCH(-1)	0.932703	0.005353	174.2232	0.0000*
Schwarz criterion	-6.679800	Akaike info criterion		-6.692165

Note. *Significant at 5% level and ** Significant at 10% level

Table 6. Results of Correlogram Squared Residuals for *RFUTIDX* (TGARCH (1, 1))

Sample: 1 3003

Included observations: 3001

Autocorrelation	Partial Correlation	AC	PAC	*Q*-Stat	Prob*
| |	| |	1-0.024	-0.024	1.6974	0.193
| |	| |	2-0.015	-0.016	2.4159	0.299
| |	| |	30.011	0.010	2.7555	0.431
| |	| |	40.031	0.031	5.6653	0.226
| |	| |	5-0.022	-0.021	7.1880	0.207
| |	| |	6 0.017	0.017	8.0502	0.234
| |	| |	7 0.002	0.001	8.0592	0.327
| |	| |	8-0.014	-0.014	8.6705	0.371
| |	| |	9-0.007	-0.007	8.8171	0.454
| |	| |	10 0.025	0.023	10.722	0.380
| |	| |	11-0.010	-0.009	11.052	0.439

| |	| |	12-0.014	-0.013	11.659	0.473
| |	| |	13 0.015	0.013	12.301	0.503
| |	| |	14 -0.004	-0.005	12.346	0.579
| |	| |	15 0.004	0.007	12.405	0.648
| |	| |	16-0.004	-0.004	12.443	0.713
| |	| |	17-0.013	-0.015	12.992	0.737
| |	| |	18-0.008	-0.007	13.189	0.780
| |	| |	19-0.004	-0.005	13.233	0.826
| |	| |	20 0.030	0.029	15.943	0.720
| |	| |	21-0.011	-0.008	16.298	0.753
| |	| |	22 0.002	0.003	16.309	0.800
| |	| |	23 0.005	0.004	16.397	0.838
| |	| |	24-0.009	-0.010	16.656	0.863
| |	| |	25-0.024	-0.023	18.343	0.828
| |	| |	26 0.005	0.002	18.414	0.860
| |	| |	27-0.005	-0.005	18.492	0.888
| |	| |	28-0.020	-0.018	19.646	0.877
| |	| |	29 0.004	0.004	19.707	0.902
| |	| |	30-0.012	-0.015	20.140	0.913
| |	| |	31 0.001	0.004	20.146	0.933
| |	| |	32-0.011	-0.010	20.481	0.942
| |	| |	33-0.009	-0.012	20.705	0.953
| |	| |	34 0.017	0.019	21.580	0.951
| |	| |	35 0.025	0.025	23.463	0.931
| |	| |	36-0.005	-0.003	23.537	0.945

Note. *Probabilities may not be valid for this equation specification.

Table 7. Results of Correlogram Squared Residuals for *RMCXCOMDEX* (GARCH (1, 1))

Sample: 5/13/2006 6/13/2018

Included observations: 3485

Autocorrelation	**Partial Correlation**	**AC**	**PAC**	***Q* - Stat**	**Prob***
| |	| |	1 0.013	0.013	0.5667	0.452
| |	| |	2 0.030	0.029	3.6296	0.163
| |	| |	3-0.001	-0.001	3.6307	0.304
| |	| |	4-0.024	-0.024	5.5745	0.233
| |	| |	5-0.018	-0.018	6.7284	0.242
| |	| |	6 0.025	0.027	8.8593	0.182
| |	| |	7-0.004	-0.003	8.9087	0.259
| |	| |	8-0.030	-0.032	12.078	0.148
| |	| |	9 0.019	0.019	13.276	0.150
| |	| |	10-0.006	-0.003	13.389	0.203

11	-0.002	-0.002	13.403	0.268
12	0.029	0.027	16.359	0.175
13	-0.013	-0.014	16.962	0.201
14	0.004	0.005	17.022	0.255
15	-0.014	-0.015	17.727	0.277
16	-0.022	-0.021	19.438	0.247
17	-0.017	-0.014	20.468	0.251
18	0.007	0.007	20.657	0.297
19	0.032	0.033	24.199	0.189
20	0.008	0.006	24.398	0.225
21	-0.011	-0.016	24.831	0.255
22	-0.012	-0.010	25.324	0.282
23	0.001	0.004	25.332	0.333
24	0.012	0.012	25.856	0.360
25	-0.020	-0.022	27.220	0.345
26	0.011	0.010	27.638	0.376
27	-0.004	-0.000	27.708	0.426
28	-0.030	-0.030	30.859	0.323
29	-0.009	-0.009	31.130	0.359
30	-0.006	-0.006	31.270	0.402
31	-0.014	-0.014	32.009	0.416
32	-0.004	-0.006	32.068	0.463
33	-0.006	-0.008	32.186	0.507
34	-0.028	-0.025	35.046	0.418
35	-0.002	-0.001	35.057	0.465
36	0.008	0.008	35.266	0.503

Note. *Probabilities may not be valid for this equation specification.

➪ **Serial Correlation :** To check whether residuals of selected models are serially correlated or not, correlogram squared residuals is applied & results for RFUTIDX and RMCXCOMDEX are outlined in the Table 6 and Table 7, respectively. Both these tables show that probability values of all Q - statistics are more than 0.05, that is, significant at the 5 %. Therefore, we accept the null hypothesis of no serial correlation.

Table 8. Heteroskedasticity Test : ARCH

(i)	**For *RFUTIDX***		
F-statistic	1.695136	Prob. *F* (1,2998)	0.1930
Obs*R - squared	1.695308	Prob. Chi-Square(1)	0.1929
(ii)	**For *RMCXCOMDEX***		
F- statistic	0.565790	Prob. *F* (1,3482)	0.4520
Obs*R - squared	0.566023	Prob. Chi-Square(1)	0.4518

➾ **Heteroskedasticity :** To check whether residuals of selected models are heteroskedastic or not, ARCH LM test is applied & results for RFUTIDX and RMCXCOMDEX are presented in the Table 8, which shows that for both the markets, probability value of *F* - statistics is more than 0.05. Therefore, we accept the null hypothesis of no heteroskedasticity & it is desirable too.

Conclusion

The objective of this paper is to examine the volatility features such as volatility clustering, persistence, and asymmetrical volatility of Indian stock (NSE) and commodity (MCX) futures market over the period from May 13, 2006 to June 13, 2018. Before applying volatility models (GARCH family models), first we need to convert non stationary series (price series) into stationary series (return series), otherwise we get spurious regression. The descriptive statistics of return series of both the markets conclude that the stock futures market has higher return as well as higher volatility in comparison to commodity futures market. However, commodity futures market's returns are more negatively skewed and have higher kurtosis than the returns of stock futures market. The present study evidences that volatility clustering (based on residual diagnostic and ARCH effect) and persistent volatility (based on GARCH) is present in both the sample markets. Further, based on TGARCH (1, 1) model, the present study concludes that only the volatility of stock futures market returns is asymmetrical and none of such features have been found in case of commodity futures market. In other words, we can say that negative news has more impact on the volatility of stock futures market as compared to positive news. Our results specifically related to stock futures market (FUTIDX) are consistent with the findings of Mall et al. (2011).

Research Implications

The outputs of the present study throw light on the behaviour of stock and commodity futures index's volatility in response to positive and negative information. This research would be helpful to investors who invest their hard earned money in the Indian stock and commodity futures market to get an idea whether both the markets reacted symmetrically or asymmetrically to positive and negative news and would also be helpful to them in investment and portfolio diversification decision making.

Limitations of the Study and Scope for Further Research

The present study examines the volatility features of stock and commodity futures market on the basis of two futures indices: FUTIDX (Nifty futures index) and COMDEX (MCX futures index). Other futures indices can be taken for the purpose of the study. Further, in addition to the TGARCH model, other asymmetrical GARCH models can be applied and intraday volatility of the underlying markets can also be analyzed to get a better understanding about the presence of symmetrical and asymmetrical behaviour of stock and commodity futures markets' volatility.

References

Abounoori, E., & Nademi, Y. (2011). The asymmetric effect of news on Tehran Stock Exchange volatility. *International Journal of Trade, Economics and Finance, 2*(4), 323 - 325. DOI: 10.7763/IJTEF.2011.V2.125

Al - Najjar, D. (2016). Modelling and estimation of volatility using ARCH/GARCH models in Jordan's stock market. *Asian Journal of Finance & Accounting, 8* (1), 152 - 167. DOI:10.5296/ajfa.v8i1.9129

Amudha, R., & Muthukamu, M. (2018). Modelling symmetric and asymmetric volatility in the Indian stock market. *Indian Journal of Finance, 12* (11), 23 - 36. DOI : 10.17010/ijf/2018/v12i11/138196

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics, 31*(3), 307 - 327. DOI: https://doi.org/10.1016/0304-4076(86)90063-1

Bollerslev, T., Engle, R., & Nelson, D. (1994). ARCH models. In R. Engle, & D. McFadden (eds.), *Handbook of econometrics* (Chap.4, pp. 2959 - 3038). Amsterdam : North Holland Press.

Gil - Alana, L.A., & Tripathy, T. (2014). Modelling volatility persistence and asymmetry : A study on selected Indian non-ferrous metals markets. *Resources Policy, 41,* 31-39. DOI: https://doi.org/10.1016/j.resourpol.2014.02.004

Mall, M., Pradhan, B.B., & Mishra, P. K. (2011). Volatility of India's stock index futures market: An empirical analysis. *Researchers World : Journal of Arts, Science & Commerce, 2*(3), 119 - 126.

Mattack, T., & Saha, A. (2016). A study on the volatility effects of listing of equity options and equity futures in National Stock Exchange of India. *Indian Journal of Finance, 10* (4), 29 - 40. DOI: 10.17010/ijf/2016/v10i4/90798

Musunuru, N. (2016). Examining volatility persistence and news asymmetry in soybeans futures returns. *Atlantic Economic Journal, 44,* 487 - 500. DOI 10.1007/s11293-016-9517-3

Natchimuthu, N., & Prakasam, K. (2018). Estimation of conditional volatility models for Indian stock market. *Asian Journal of Research in Business Economics and Management, 8* (5), 33 - 48. DOI: 10.5958/2249-7307.2018.00045.2

SEBI. (n.d.). *Securities Contracts (Regulation) Act, 1956.* Retrieved from http://sebi.gov.in/acts/contract.pdf

Singh, V. K., & Ahmad, N. (2011). Modelling S&P CNX nifty index volatility with GARCH class volatility models: Empirical evidence from India. *Indian Journal of Finance, 5* (2), 34 - 47.

Srikanth, P. (2014). Modeling asymmetric volatility in Indian stock market. *Pacific Business Review International, 6* (9), 87 - 92.

Varughese, A., & Mathew, T. (2017). Asymmetric volatility of the Indian stock market and foreign portfolio investments : An empirical study. *Indian Journal of Finance, 11*(6), 36 - 49. DOI: 10.17010/ijf/2017/v11i6/115595

Zakoian, J. - M. (1994). Threshold heteroskedastic models. *Journal of Economic Dynamics, 18* (5), 931 - 955.

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INDIAN JOURNAL OF FINANCE

Statement about ownership and other particulars about the newspaper "INDIAN JOURNAL OF FINANCE" to be published in the 3rd issue every year after the last day of February.

FORM 1V

(see Rule 18)

1. Place of Publication	:	NEW DELHI
2. Periodicity of Publication	:	MONTHLY
3. 4,5 Printer, Publisher and Editor's Name	:	S. GILANI
4. Nationality	:	INDIAN
5. Address	:	Y-21,HAUZ KHAS, NEW DELHI - 16
6. Newspaper and Address of individual	:	ASSOCIATED MANAGEMENT
Who owns the newspaper and partner of	:	CONSULTANTS PRIVATE LIMITED
Shareholder holding more than one percent.	:	Y-21, HAUZ KHAS, NEW DELHI - 16

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Sd/-

Dated : March 1, 2019

S. Gilani

Signature of Publisher