Analyzing the Impact of CNX Nifty Index Futures on the Volatility of S&P CNX Nifty Index

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Abstract

Volatility plays an important role in the stock market. Investment decisions are made based on the volatility, apart from other significant factors like price, volume traded, liquidity, etc. Many new instruments have been introduced in the Indian stock market in the recent years to satisfy the needs of the investors and to enhance market efficiency. Index futures trading is one such instrument introduced in the year 2000 to reduce the systematic risk, improve investment strategy, and to achieve more efficient price discovery. Despite a continuous increase in the turnover of the index, futures trading raises the question, whether the equity market volatility increased or not due to the introduction of index futures. So, the present study examined the effect of futures trading on volatility of CNX Nifty. The study period was divided into pre-futures period and post-futures period. GARCH model was used to measure the volatility of CNX Nifty returns in pre-future period and post-future period separately. The results of the study indicated that introduction of index futures trading reduced CNX nifty volatility.

Keywords : **nifty, nifty futures, volatility, GARCH, descriptive analysis**

JEL Classification : C22,G10,G15,G17

Paper Submission Date : October 27, 2016 ; Paper sent back for Revision : December 5, 2016 ; Paper Acceptance Date : December 26, 2016

NSE and BSE are the leading stock exchanges in India. Bombay Stock Exchange is the oldest stock exchange in Asia with a rich legacy. The BSE has over 874 brokers across the country while NSE has more than 1000 members. NSE's liquidity is better than that of BSE. The NSE is the largest stock exchange in India in terms of daily turnover and number of trades. For example, Bajaj Auto is traded in both the markets and comparing its trading volume on September 2, 2005 revealed that the BSE trading volume of Bajaj Auto was 26,000 shares and NSE trading volume of Bajaj Auto was 14 lakhs, which is 50 times more than that of BSE.

The derivative contract was introduced in the year 2000 at BSE and NSE. Derivatives provide a platform to the participants for hedging their real or potential exposure, speculating on the degree and the direction of the movement in underlying variables, finding and exploiting arbitrage opportunities arising out of temporary mispricing of various derivative products (Joshipura, 2009). After introduction of derivative segment, the BSE gave up market share to the NSE little by little every year since 2000. This motivated us to consider the CNX Nifty and Nifty futures for this study.

Review of Literature

Most of the literature in the past compared the volatility of the spot market before and after the introduction of

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futures and also tested the variations in volatility in the view of market information. ARCH time series techniques are mostly applied as a measure of volatility. The impact of volume, open interest, and information content on the underlying markets was tested. As far as foreign countries such as South Africa, Taiwan, and UK markets are concerned, in general, the studies showed evidence of increased stock market volatility due to introduction of futures contracts. Some studies gave little or no evidence of increased volatility in spot market.

The review of these literature gave an idea to us about the nature of future trading activity and various tools used to measure the volatility of the spot market. The Table 1 and Table 2 disclose the major findings of the literature discussed here.

Table 1. Earlier Studies on Relationship Between Futures Trading Activity and Stock Price Volatility in India

S. No.	Author(s)	Year	Period of the Study	Tools Applied	Outcome of the Study
1	Gupta	2002	2000 to 2002	Parkinson's extreme value estimator & Garman-Klass volatility measure	The overall volatility of the stock market dropped after the introduction of the futures in Nifty and Sensex.
2	Thenmozhi	2002	2000 to 2002	Descriptive analysis	Futures trading significantly reduced the volatility of spot index returns and spot index returns do not lead futures index returns.
3	Thiripalraju & Patil	2002	1999 to 2001	ARCH model	Volatility was reduced in the Spot index as well as its underlying stocks after the introduction of index futures in the Indian capital market.
4	Hetamsaria & Deb	2004	1999 to 2003	GARCH models	Introduction of futures contracts result in a reduction in spot market volatility.
5	Pati	2008	2001 to 2007	ARMA-GARCH ARMA GJR-GARCH	Futures price volatility is positively related to expected and unexpected components of volume.
6	Debasish & Das	2009	2001 to 2007	WRS test and KS-test	Sensex volatility increased after introduction of futures contract.

Table 2. Earlier Studies on Relationship Between Futures Trading Activity and Stock Price Volatility in Foreign Studies

S.No	Author(s)	Year	Country	Period of the Study	Tools of the Study	Outcome of the Study
1	Hodgson & Nicholls	1991	Australia	1981 to 1987	Standard Deviation	Introduction of futures trading has not affected the long-term volatility of spot index.
2	Kamara, Miller, & Siegel	1992	America	1976 to 1987	WRS test and KS-test	Futures trading is not the reason for increased volatility in S&P 500 Index.
3	Antoniou & Holmes	1995	United Kingdom	1980 to 1991	GARCH family Model	Futures trading has led to increased volatility in spot market.
4	Smit & Nienaber	1997	South African	1991 to 1994	Regression Analysis	Increased trading in futures market causes larger volatility in spot market.
5	Wang & Lu	2005	Taiwan	1996 to 2002	variable GJR-M model	Conditional volatility in Taiwan market increased after introduction of futures.
6	Xie & Huang	2014	China	2005 to 2012	GARCH-M model	An Index future does not have a significant effect on the magnitude of spot price volatility.

Objective of the Study

Considering the existing literature review and the problem statement, the following objective was framed for the study :

- To measure the impact of CNX Nifty index futures on the volatility of S&P CNX nifty index.

Methodological Framework

(1) Problem Statement : The derivatives contract was introduced with the objective of risk transfer, increase in liquidity, and ensuring best market efficiency (Choksi, 2010). Derivative trading started in India from June 2000 with the introduction of index future followed by other derivative products that were introduced sequentially. The CNX Nifty index value was nearly 1471 points in the period of index future introduction. Later, it gradually increased and touched 9000 points in the year 2015. The current calendar year also saw huge swings in the benchmark indices i.e. the CNX Nifty traded between a high of 8,914.30 and a low of 7,558 points. In the year 2015 the derivatives turnover is more than 15 times the cash market. It was less than 10 times in the year 2011.The rise in the derivative turnover coincided with increased volatility in the equity market. As a consequence, traders and investors are increasingly placing their bets in the derivatives segment, leading to a quick rise in the segment's turnover compared to the cash market. This leads to the question whether the index future trading makes the cash segment more volatile or less volatile.

(2) Research Methodology : Stock price volatility plays a crucial role in the stock market. There are different opinions regarding the impact of futures on the underlying spot index which is revealed in literature. This motivated us to get an idea about the effect of future trading activity on Nifty price volatility. So, this part of the analysis was used to test whether future trading activity increases stock price volatility or decreases stock price volatility. For this purpose, the daily closing price of the CNX Nifty index is converted into log return. The Nifty daily closing price is collected from July 1990 to December 2015 and the whole period was segregated as pre-future and post-future.

(i) Descriptive Statistics : Descriptive statistics is the calculated report of the mean, standard deviation, minimum, and maximum return in the sample period, skewness, and kurtosis. Mean is the average value of the sample data, which is obtained by adding the total number of data value and dividing it by the number of observations. Median is the middle value of the sample data. The middle value of the data series is calculated by sorting of values from the smallest to the largest. The median is a center of the distribution.

Standard deviation is a measure how spread out the sample data is from the mean. The standard deviation is calculated by :

$$S = \frac{\sqrt{\Sigma_{i=1}^{N} (y_i - \bar{y})^2)}}{N - 1} \quad (1)$$

Skewness is a measure of asymmetry of the distribution of the data around its mean. Skewness is calculated as :

$$S = \frac{1}{N} \sum_{i=1}^{N} \left(\frac{y_i - \bar{y}}{\sigma} \right)^3 \quad (2)$$

where,

σ is the standard deviation; the standard deviation is taken from the variance ($\sigma = \sqrt{S(N\text{-}1/N)}$). The skewness of a normal distribution is zero. The right side tapped distribution is called as positive skewness which has a long right tail and the left side tapped distribution is called negative skewness which means that the distribution has a long left tail.

Jarque-Bera is a statistic for testing whether the series is normally distributed or not. The test statistic is calculated as the difference between skewness and kurtosis of data from normal distribution. The statistic is computed as :

$$\text{Jarque - Bera} = \frac{N}{6}\left(S^2 + \frac{(K-3)^2}{4}\right) \qquad (3)$$

The test probability is the probability of Jarque-Bera statistic. A p - value less than 0.05 leads to rejection of the null hypothesis and acceptance of alternative hypothesis.

(ii) Stationary Test : Time series analysis is applied only when sample data supports the stationary property. The non-stationary series can be converted into stationary series by taking the first order difference $I(1)$ or second order difference $I(2)$. Dickey-Fuller test was developed by statisticians David Dickey and Wayne Fuller in 1979 which failed to control the auto correlation in residual term. They developed another model called augmented Dickey Fuller Test (ADF) to remove auto correlation issue in residual part (Enders, 2010).

Three equation of ADF test are :

$$\Delta Y_t = B_1 + ZY_{t\text{-}1} + a_i + e_t \rightarrow \text{Intercept only} \qquad (4)$$

$$\Delta Y_t = B_1 + B_{2t} + ZY_{t\text{-}1} + a_i + e_t \rightarrow \text{Trend \& } i\text{Intercept} \qquad (5)$$

$$\Delta Y_t = ZY_{t\text{-}1} + a_i + e_t \rightarrow \text{No Trend \& no intercept} \qquad (6)$$

Commonly, unit root test is used to test the stationary of time series data. Many unit roots tests are available to check stationary hence, this study used augmented Dickey- Fuller test. The auto correlation problem is tackled by the ADF test. The ADF test is preferred when data contains more negative value. The number of augmenting lags value is determined by minimizing the Schwartz Bayesian information criterion in the ADF test. In ADF test, lags go down until the last lag is statistically significant.

(iii) Serial Correlation Test : Serial correlation theory said that in time series regressions analysis, the residuals are correlated with their own lagged values. This serial correlation theory violates the standard assumption of regression theory that disturbances are not correlated with other disturbances. Serial correlation test is a measure of relationship between successive errors in the residuals. Two type of serial correlation tests are applied in this section of the study.

(iv) Breusch-Godfry LM Test : The Breusch-Godfrey serial correlation LM test is a test for analyzing serial correlation in the error terms of the regression model. This is a general test for serial correlation of any order i.e. residuals may be correlated over for more than one period. The test statistic is computed from original regression equation :

$$Y_t = b_0 + b_1 X_t + u_t \qquad (7)$$

where,
b is the estimated coefficients and u_t is the error term. The Breusch-Godfrey LM Test is applied to residual part which is derived from the regression equation.

$$u_t = \rho_1 u_{t-1} + \rho_2 u_{t-2} + \rho_3 u_{t-3} + \ldots \rho_q u_{t-q} + e_t \quad (8)$$

ρ is the time period of residuals correlated. The null hypothesis denotes that there is no serial correlation of any order up to p.

(v) Correlogram and Ljung Box Q Statistic : Correlogram view shows the auto correlation (AC) and partial auto correlation (PAC) functions up to the specified order of lags. The last two columns displayed in the correlogram are the Ljung-Box *Q*-statistics and corresponding p-values. The *Q*-statistic at specified lag is a test statistic for the null hypothesis. The null hypothesis denotes there is no serial correlation upto the specified log order. The auto correlation function and partial auto correlation functions are useful qualitative tools to assess the presence of auto correlation at individual lags in Ljung-Box test. The Ljung-Box Q-test is a quantitative way to test for auto correlation at multiple lags together (Ljung & Box, 1978).

(vi) Heteroscedasticity Test : If the error terms do not have constant variance, there is heteroscedasticity. The ARCH test is a Lagrange multiplier (LM) test for autoregressive conditional heteroscedasticity (ARCH) in the residuals (Engle, 1982). This particular heteroscedasticity is mentioned in the number of financial time series study. This suggests the error term is normally distributed with zero mean and conditional variance depending on the squared error term lagged one time period. The conditional variance is the variance given the values of the error term lagged once, twice etc.

The ARCH LM test statistic is computed from a regression test. To test the null hypothesis of there is no ARCH effect up to order k in the residuals, we run the regression analysis. The ARCH effect testing equation for the residual part is :

$$e^2_t = \beta_0 + (\Sigma^k_{\delta=1} \beta_\delta e^2_{t-\delta}) + v_t \quad (9)$$

To test the constant variance, ordinary least square regression is executed which is a regression of the squared residuals on constant and lagged squared residuals up to order k. Where, e^2_t is the residual, β_0 is regression coefficient, and v_t is the disturbance term.

(vii) GARCH Model : The problem of applying the usual ARCH model is that it requires many lags to model the process correctly and the non-negativity of coefficient may be violated. To avoid the long lag structure of the ARCH (q) developed by Engle in 1982, Bollerslev introduced a generalized ARCH model called GARCH in the year 1986 by adding the lagged values of the conditional variance. The mean equation is :

$$Y_t = X_t + e_t \quad (10)$$

The variance in the error term depends on the squared error terms of previous period. Thus, GARCH *(p, q)* model specifies conditional variance to be a linear mixture of q lags of squared residuals (ε_{t-1}) from the conditional return equation and p lags from the conditional variance σ_{t-1}. Then, the GARCH *(p, q)* specification may be written as follows :

$$\sigma^2_t = \beta_0 \sum_{i=1}^{q} \beta_1 \varepsilon^2_{t-1} + \sum_{j=1}^{p} \beta_2 \sigma^2_{t-1} \quad (11)$$

where, the coefficients $\beta_1\beta_2 > 0$ and $(\beta_1 + \beta_2) < 1$ and the estimation of the conditional variance by using the following equation :

$$\sigma^2_t = \beta_0 + \beta_1 \sum t^2 + \alpha_1 \sigma^2_{t-1} \qquad (12)$$

Here, $\beta_1 \Sigma t^2$ is ARCH term. The ARCH term is the news about volatility from previous period which is measured as the lag of squared residual derived from the mean equation. $\alpha_1\sigma^2_{t-1}$ is the GARCH term which denotes conditional variance.

(viii) Diagnostic Test : The selected model needs to be verified for fitness. The residual part of GARCH model is tested by Correlogram for squared residuals and ARCH LM test. If the GARCH model is well stated, then the standardized residuals are independent and identically distributed.

Empirical Analysis and Discussion

This economic analysis is used to test whether future trading activity increases stock price volatility or reduces it. CNX Nifty is treated as the principal stock index of the country. Hence for analysis, CNX Nifty was selected. The closing price of the CNX Nifty index is converted into log return. The reason for considering log return is unequal raw data termed as equal values. To examine the effect of futures trading on volatility in Nifty and GARCH family techniques were employed in this study.

(1) Descriptive Statistics and Normality Test : Descriptive statistics is used to define basic characteristics of the data which provides simple statistical summary of the data. Normality tests are used to determine whether the data set has normal distribution or not. Many methods are used to test normality of the data. In this study descriptive statistic with Jarque-Bera test was used. Table 3 shows the descriptive statistics and normality test of CNX Nifty returns from July 1990 to December 2014. The skewness for post-future period is negative and also small in absolute value, indicating that the distribution is slightly skewed to the left. In the pre-future the value of skewness is 0.075232 which is positively skewed. The normal distribution has kurtosis value of three but nifty return has kurtosis values 7.818270 and 11.65699 which are more than double and four times of normal distribution value. The nature of the kurtosis is leptokurtic.

H_0: The data are normally distributed.
H_1: The data are not normally distributed.

The Jarque-Bera test is created based on the theory that skewness and kurtosis of normal distribution are equal to zero. The null hypothesis of the Jarque-Bera test is the joint hypothesis of the skewness being zero and the excess kurtosis being zero. Table 3 shows that skewness and kurtosis are not equal to zero hence, the data are not normally distributed in both the periods. The probability value is zero which is less than 5%, so the null hypothesis of Jarque-Bera test is rejected and the alternative hypothesis is accepted. Nifty returns are not normally distributed in pre-future period as well as post-future period.

Standard deviation is the traditional measure of volatility. Volatility is traditionally measured by using closing

Table 3. Descriptive Statistics of CNX Nifty

Period	Mean	Std. Deviation	Skewness	Kurtosis	Jarque-Bera	Probability
Pre -future	0.073152	1.949892	0.075232	7.818270	2196.994	0.000000
Post -future	0.048189	1.539314	-0.285601	11.65699	11384.56	0.000000

price of data; hence, this method is also called the classical estimator or the optimal estimator which is obtained from random walk model. Volatility of nifty return has been reduced from 1.949892 in pre-future period to 1.539314 in the post-future period. This result is similar with that of Thenmozhi (2002). The standard deviation value is low in the post-future period. So, the introduction of Nifty future reduced the stock price volatility and stabilized the stock market. The standard deviation has some limitations in measuring the volatility as well. Standard deviation alone is not sufficient to decide whether Nifty future reduces stock price volatility which is additionally analyzed by GARCH model because Nifty return distribution is leptokurtic in nature. If the time series follows the characteristics of Leptokurtosis, it would able to measure the volatility by using non-linear model such as ARCH/GARCH.

(2) Stationary : Stationary property is very essential for all-time series modeling. The simplest way to test the stationary of the series is to plot the graph for the selected variables. Fig. 1 denotes the graphical representation of the CNX Nifty return for pre-future period and post-future period. In this figure there is no trend pattern in any one period, indicating that the data series are stationary at both the periods. Nifty return fluctuated around the mean. So, nifty returns have constant mean and variance over the period. From the figure we assume that the data is stationary which is verified by the ADF test. The ADF test is employed to assess the stationary of the CNX Nifty Return.

Figure 1. Graph of Nifty Returns

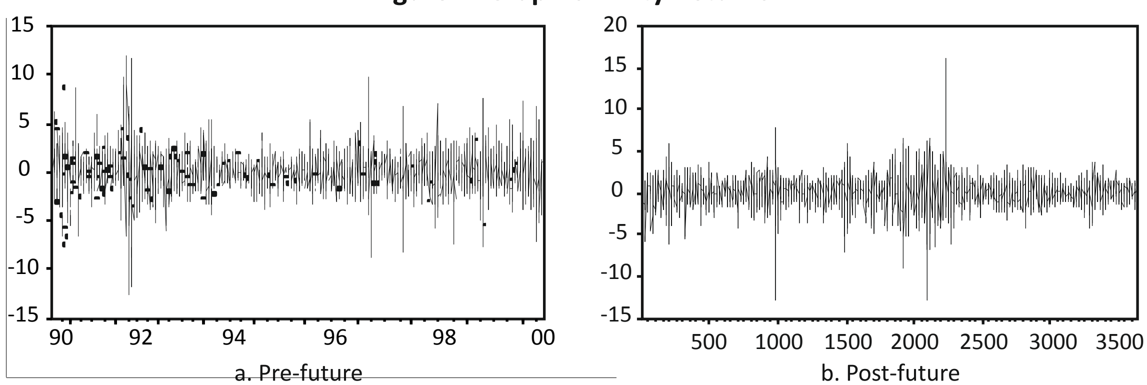


Table 4. ADF Test of Nifty Returns

Pre-future			
At Level		***T*-Statistic**	**Probability**
Augmented Dickey-Fuller test statistic		-42.50295	
Test critical values:	1 % level	-3.433037	0.0000
	5 % level	-2.862613	
	10 % level	-2.567387	
Post-future			
At Level		***T*-Statistic**	**Probability**
Augmented Dickey-Fuller test statistic		-43.02914	
Test critical values:	1 % level	-3.431966	0.0000
	5 % level	-2.862139	
	10 % level	-2.567133	

H_0: Data is not stationary.
H_1: Data is stationary.

The log order is specified by the Schwarz information criterion (SIC). Table 4 shows that the values of the ADF test statistics are less than the critical value at 1%, 5%, and 10% significant level, indicating that the Nifty returns are stationary in all the periods. The *p* value of the ADF test is less than 5%, denoting the rejection of null hypothesis. Therefore, the data series are directly stationary without differentiating. Once the data series are stationary, the next step is model identification for measuring volatility.

(3) Residual Analysis : Figure 2 shows that the returns series fluctuates around the mean values, which are close to zero. The small up and down movements are followed by more up and down movements. High up and down movements are followed by other high up and downs.

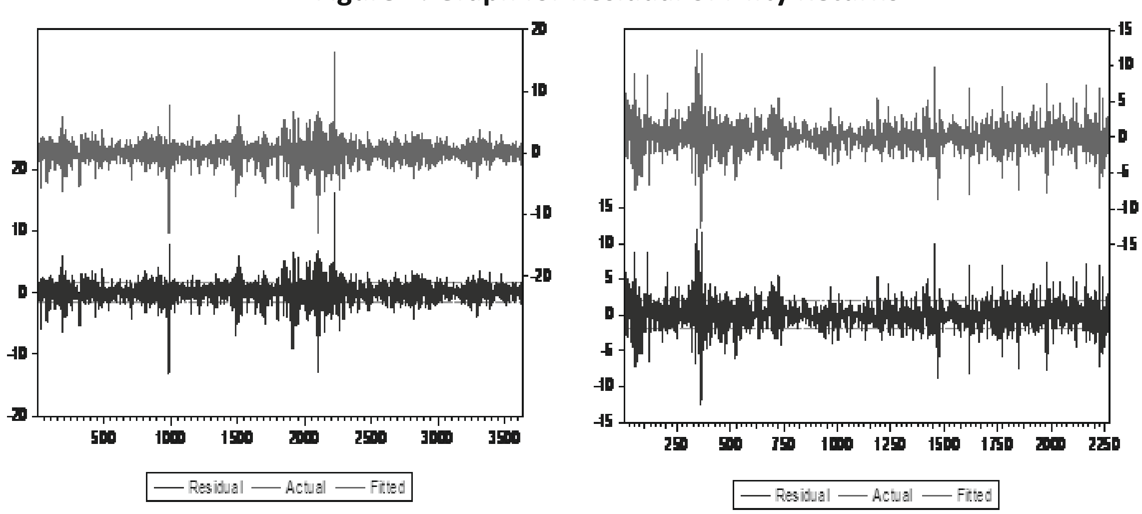
Volatility clustering is assumed in the above figure because the small fluctuation is creating another small fluctuation for a long time period and the high fluctuation is creating another high fluctuation. Statistically, volatility clustering implies a strong auto correlation in squared return which is tested by serial correlation and the Arch effect is tested by heteroscedasticity test.

(4) Serial Correlation Test : The residuals part generated from Ordinary Least Squares (OLS) regression equation is employed to test serial correlation.

H_0: Residuals are not serially correlated.
H_1: Residuals are serially correlated.

The Correlogram and Q statistic is the basic test for checking serial correlation which is shown in the Table 5. In this test the auto correlations and partial auto correlations of the residuals are generated up to the specified number of lags with Q statistics. The system specified log is 36 for this test. The probability value of Q statistics is significant at the maximum specified log. Therefore, the null hypothesis is rejected. One more test namely, Breusch-Godfrey serial correlation LM test is also used to check serial correlation.

Figure 2. Graph for Residual of Nifty Returns



a. Pre-future

b. Post-future

Table 5. Serial Correlation Test of Nifty Returns

Test	Pre-future	Post-future
Correlogram and Q statistics		
Ljung Box Q Statistic	103.15	88.104
P - value of Q Statistic	0.0000	0.0000
Breusch-Godfrey serial correlation LM		
Serial correlation LM test		
Prob. of Chi square (2 df)	0.0000	0.0000

Table 6. Heteroscedasticity Test

Pre-future			
F-statistic	167.8956	Prob. *F* (1,2266)	0.0000
Obs*R - squared	156.4517	Prob. Chi-Square(1)	0.0000
Post-future			
F-statistic	199.1327	Prob. *F* (1,3627)	0.0000
Obs*R-squared	188.8729	Prob. Chi-Square(1)	0.0000

The *p* value Breusch-Godfrey serial correlation LM rejects the null hypothesis at 5% significance level. The specified log length is two in the LM test. This test regresses the residuals on original regressor and lagged residual upto the specified log order. Both the test, Correlogram and LM test reject null hypothesis at 5% significance level denoting that residuals are serially correlated in pre-future and post-future period.

(5) Heteroscedasticity Test : The ARCH test regresses the squared residuals on lagged squared residuals and a constant.

H_0: There is no ARCH effect.
H_1: There is ARCH effect.

The *p* value of the heteroscedasticity test is less than 0.05 (Table 6). Therefore, the null hypothesis is rejected and the alternative hypothesis in both the periods is accepted. The log return of Nifty is heteroscedastic in nature. The Nifty return investigation shows volatility clustering or persistence (Chris, 2002). If return series has property like serial correlation and heteroscedasticity, then we can use ARCH/GARCH model to obtain time varying volatility (σ^2) based on past history.

(6) GARCH Model : GARCH (1, 1) model is usually used to describe financial time series fluctuation (Zivot & Wang, 2006). Moreover, existing studies show that GARCH (1, 1) provides the most robust estimates (Hansen & Lunde, 2005). Various GARCH family models like GARCH (1, 1), GARCH (1, 2), GARCH (2, 2), GARCH (2, 1) are applied to measure the volatility based on the significance of each model and AIC value; GARCH (1, 1) is found to be fitted model. Based on the previous studies and AIC value; GARCH (1, 1) model was selected to measure the volatility of nifty return. Volatility is measured separately for pre-future period and post-future periods by performing joint estimation of mean equation and variance equation. The result of GARCH (1, 1) is presented in the Table 7.

Table 7. GARCH (1, 1) Model for Nifty Returns

Variable	Coefficient	Std. Error	z-Statistic	Prob.
		Pre-future		
C	0.077601	0.014009	5.539416	0.0000
RESID(-1)^2	0.092731	0.009141	10.14432	0.0000
GARCH(-1)	0.889457	0.008565	103.8436	0.0000
		Post-future		
C	0.052063	0.006152	8.463019	0.0000
RESID(-1)^2	0.124145	0.008051	15.41915	0.0000
GARCH(-1)	0.856248	0.008671	98.75075	0.0000

The conditional variance equation of the GARCH (1, 1) model is GARCH = C (2) + C (3)*RESID (-1) ^2 + C (4)*GARCH (-1) which also denoted as $\sigma t^2 = \beta_0 + \beta_1 \Sigma t^2 + \alpha_1 \sigma^2_{t-1}$ in Equation (12).

In Table 7 , RESID (-1)^2 represents the ARCH term which is denoted by β_1 in the variance equation and GARCH (-1) represents the GARCH term which is denoted as $\alpha_1$in variance equation. The ARCH term is significant at 1% level. This shows that recent past information is creating a positive impact on volatility. The value of ARCH term (β_1) is increased from 0.092731 to 0.124145 in the post-future period. This indicates that the information efficiency increased in Nifty due to information content of nifty future price. This increased efficiency leads to a greater reaction to news. This implies that the introduction of future trading improves the quality of information flowing to Nifty and Nifty prices accordingly reflect more prompt changes that occur in demand and supply conditions (Debasish, 2009).

The α_1 value before the introduction of Nifty future is 0.88 whereas, after the introduction of Nifty future it is 0.85. The reduced α_1 value indicates that volatility is reduced in the post-future period. This implies that information is impounded more slowly after the introduction of nifty futures. The addition of α_1 and β_1 is 0.982188 in pre-future period, and the addition of α_1 and β_1 is 0.980393 in post-future periods indicating that volatility of Nifty decreased after the introduction of Nifty futures. This finding supports the result of Chen, Han, Li, and Wu (2013). The sum of the ARCH and GARCH coefficients (α_1+β_1) is very close to one, indicating that volatility shocks are quite persistent.

(7) Diagnostic Test for the GARCH (1, 1) Model

(i) Auto Correlation Test : The residual of the GARCH model should be independent; it is free from auto

Table 8. ARCH Test

	ARCH test for Pre-future period		
F-statistic	0.689433	Probability *F*(1,2266)	0.4064
Obs**R*- squared	0.689831	Probability of Chi. Square (1)	0.4062
Durbin-Watson statistic	1.999240		
	ARCH test for Post-future period		
F-statistic	0.702114	Probability *F* (1,2266)	0.4021
Obs**R*- squared	0.702360	Probability of Chi. Square (1)	0.4120
Durbin-Watson statistic	2.000176		

correlation and heteroscedasticity effect. The auto correlation effect is tested by Q-statistics of the squared standardized residuals. The result of Correlogram squared residuals is presented.

H_0: There is no auto correlation.
H_1: There is an auto correlation.

The auto correlation and partial auto correlation series are closer to zero and the *p*-value of the Q-static is not significant. The *p* - values from log 1 to log 36 are nearly more than 0.05 at all log levels. Hence, we cannot reject the null hypothesis, rather the null hypothesis is accepted for both the periods. The GARCH (1, 1) model does not have auto correlation.

(ii) Heteroscedasticity Test : The residual part of the GARCH (1, 1) model is free from auto correlation. ARCH LM test is applied to check heteroscedasticity. Table 8 shows the test result. The probability value of *F* - statistic and Chi square test statistic is more than 5% significance level. Therefore, the null hypothesis can't be rejected. So, GARCH (1, 1) model does not contain ARCH effect. The estimated model is a good model for measuring volatility in the pre-future period as well as post-future period.

H_0: There is no ARCH effect.
H_1: There is ARCH effect.

Findings

The ADF test result indicates that the CNX Nifty return is stationary at level in pre-future period and post-future periods. The descriptive statistics show that the standard deviation of Nifty return has been reduced from 1.949892 in pre-future period to 1.539314 in the post-future period. The standard deviation value is low in the post-future period, so the introduction of Nifty future reduces stock price volatility and tries to stabilize the stock market. The residual analysis of Nifty returns indicates that volatility clustering is appearing in the return series. The ARCH and serial correlation tests indicated that Nifty return series are serially correlated and have the ARCH effect in pre-future as well as post-future period.

The result of GARCH (1, 1) model indicates that β_1 value increased from 0.092731 to 0.124145 in the post-future period meaning that the introduction of future trading improves the quality of information flowing to Nifty, and Nifty prices promptly reflect changes that occur in demand and supply conditions. The reduced β_1 coefficient of lagged variance term implies that futures trading is expected to lead a reduction in uncertainty regarding previous day news. The α_1 value before the introduction of Nifty future is 0.88 whereas, after the introduction of Nifty future it is 0.85. This implies that information is impounded more slowly after the introduction of Nifty futures. The addition of α_1 and β_1 is 0.982188 in pre-future period, and the addition of α_1 and β_1 is 0.980393 in post-future periods indicates that volatility of Nifty decreased after the introduction of Nifty futures trading.

Conclusion and Research Implications

The study discloses that CNX Nifty volatility is reduced after the introduction of future contract. The short selling, lower margin, and lower transaction costs in the future trading makes more traders and speculators move to the future market. Due to this the future market is termed as more volatile as compared to equity market. Volatility of Nifty return has been reduced from 1.949892 in pre-future period to 1.539314 in the post-future period. The standard deviation value is low in the post-future period. So, the introduction of Nifty future reduced the stock price volatility and stabilized the stock market. The value of ARCH term β_1 increased from 0.092731 to

0.124145 in the post-future period. This indicates that information efficiency increased in Nifty due to information content of Nifty future price. This increased efficiency will lead to a greater reaction to news. This implies that the introduction of future trading improves the quality of information flowing to Nifty and reduces CNX Nifty volatility.

Limitations of the Study and Scope for Further Research

Although the research has outstretched its aims, there were some unavoidable limitations. The CNX Nifty is used as a representative of the Indian equity market even though the Sensex represents the Indian stock market movement. However NSE, has nearly 75% total cash segment of stock market capitalization which is not an exact representation of the stock market in India.

Volatility in the option segment is much higher than the future segment of derivative market, but rarely studies have been conducted in this area. It will be very useful for investors, fund managers, and policy makers if research is conducted to study the impact of option trading in the Indian stock market volatility. This study used index closing price of Nifty and Nifty future for measuring volatility, but further studies may be conducted on scrip level analysis, inter sector analysis, and inter market analysis may be useful to capture specific impact.

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