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PAPER

A Study of Market Efficiency from Option Prices Evidence from the National Stock Exchange of India

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Abstract This paper investigates the market efficiency of S&P CNX Nifty equity index options for at-the-money non-overlapping monthly implied volatilities. Under the rational expectation hypothesis, call and put implied volatilities are calculated using Black and Scholes option pricing-model for the period June, 2001 to May, 2011. The ordinary least squares estimation clearly shows that implied volatility is the best estimate of future realized volatility. An empirical result on Granger causality shows that there is only unidirectional causality prevails in the Indian options market. Granger causality test (Sims and Geweke) indicates that call and put implied volatility causes the realized volatility but realized volatility cannot cause implied volatility. Granger causality test also confirms that for Indian options market historical volatility does not subsume useful information what already contained in the option price (i.e. implied volatility). The study concludes that volatility estimates based on the option's price are the best estimate for the future volatility and useful in the pricing of derivatives and portfolio-risk-management.

Keywords Implied Volatility - Realized Volatility - Market Efficiency Information Content - Granger causality - Index options BSOPM.

JEL Classification G14

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Introduction

In the financial economics, the concept of volatility is very critical. Some author defines it as the measure of uncertainty of the financial assets or instruments traded in the capital market. In simple words it is the simple standard deviation of the returns, realized on a particular financial instrument for a given set of time. Why volatility should be studied? It is a matter of interest among the investors, financial institutions, government agency and practitioners. Generally investor analyzes the volatility for risk management, portfolio selection, valuation purpose, for designing trading strategies (such as volatility arbitrage). After the noble work of Black and Scholes in 1973 option pricing model for CBOE volatility study become more systematic for academics and practitioners. Investors generally rely on the estimates of volatility such as historical volatility also known as realized volatility, implied volatility. Historical volatility is directly observable and can be calculated daily, monthly or annually for the given financial instruments, while implied volatility cannot be observed directly, it can be inverted from the option prices, based on the Options pricing model.

In the study of superiority of historical and implied volatility (Christensen and Prabhala, 1998; Hansen, 2001; Kumar, 2008; Panda et. al. 2008 and Li and Yang, 2009) it is found that implied volatility outperforms the historical volatility. According to mean-reversion principle (Mandelbrot and Hudson, 2004) historical volatility forecast the future volatility under rational expectation that the past tends to be repeated. Historical volatility is the unconditional volatility forecast which ignores the most recent publicly available information. Therefore, historical volatility does not reveal the true volatility. Under the efficient market hypothesis it is found that implied volatility contains all the information that contained in the historical volatility. This study well explained by the superiority of implied volatility over the historical volatility by Bodie and Merton (1995).

Implied volatility is a transformation of a standard European option[1] price. It is the volatility that, when input into the Black-Scholes option pricing model (BSOPM), yields the price of the option. In other words, it is the constant volatility of the underlying process that is implicit in the price of the option. For this reason, some authors refer to implied volatility as implicit volatility. Implied volatility is an alternative way to estimate volatility to be inferred from the options market, i.e. the current volatility of a stock as reflected by its option price.

The innovative work of Black and Scholes (1973) in the line of option pricing has made possible to study implied volatility and it became most popular among the academician and practitioners. According to Black and Scholes option pricing model if the market is efficient, then implied volatility should be an unbiased and

1 European style options cannot be exercised before its maturity date. For the present study OPTIDX options of CNX Nifty index are of European style and cash settled.

efficient predictor of future *ex –post* realized volatility. Under the assumption of market efficiency and Black and Scholes option pricing model, it gives the expected volatility known as implied volatility, this implied volatility should be an unbiased and efficient predictor of future *ex –post* realized return volatility. Implied volatility should subsume the information contained in all other variable used to explain future realized volatility.

The efficiency of implied volatility as predictor of realized return volatility was discussed at great extent in the last three decades. When looking on the literature still some inconclusive evidence are present that makes this topic more contentious. There are some groups of academician and practitioners (Latané and Rendleman, 1976; Chiras and Manaster, 1978; Beckers, 1981; Day and Lewis, 1992; Jorion, 1995; Christensen and Prabhala, 1998; Hansen, 2001; Christensen and Hansen, 2002; Szakmary et al., 2003; Corrado and Miller, 2005; Kumar, 2008; Panda et al., 2008 and Li and Yang, 2009) are in the favor of implied volatility as a best predictor of future realized return volatility. While on the other hand some group of scholars they are little suspicious about market efficiency and the predictive power of implied volatility. Lamoureux and Lastrapes (1993), Canina and Figlewski (1993), Gwilym and Buckle (1999) and Filis (2009) gave mixed conclusion on the information content of option prices and the predictive power of implied volatility and the historical volatility.

However, some group of scholars Jackwerth and Rubinstein (1996), Chance (2003) and Koopman, et al. (2005) strongly oppose on the information content of implied volatility, they observed that there is no correlation between implied and realized volatility. The empirical work of these people showed that historical volatility outperforms the future realized return volatility, and historical return volatility was the best predictor of future *ex –post* realized return volatility.

The empirical work is presented as: Firstly, non-parametric test that gives the elementary results on market efficiency of implied volatility and applicability of BSOPM for OPTIDX options market. Secondly, by OLS estimation that explains how implied volatility explains the future realized volatility. Thirdly, by causality estimation using three approaches to Granger Causality Granger (1969), Sims (1972), Geweke (1983) this technique has been applied to know the direction of causality for implied and realized volatility.

The main purpose of this paper is to examine the market efficiency of S&P CNX Nifty index options and predictive power of implied volatility, implied in the options premium of OPTIDX options. In this empirical work it is found that call and put implied volatility does contain information about S&P CNX Nifty index options as best predictor of future *ex-post* realized volatility. An empirical result on Granger Causality shows that there is only unidirectional causality prevails in the Indian options market. Granger Causality test (Sims and Geweke) indicates that call and put implied volatility causes the realized volatility but realized volatility cannot cause implied volatility. Granger Causality test also confirm that for Indian options market historical volatility does not subsumes useful information what already contained in the Options price.

This paper is written as follows: Section "Data and sampling procedure" deals with data sources and sampling procedure, Section "Variable definition" explains how variables are calculated, Section "Methodology and empirical results" explain methodology and empirical results. Section "Conclusion" ends with conclusion.

Data and sampling procedure

The present study is based on the index options for S&P CNX Nifty. NSE introduced trading in index options as on June 4, 2001. The options contracts are of European type and cash settled. The study period starts from June, 2001 to May, 2011, which covers the entire period of introduction of options on derivative segment F&O's of NSE. OPTIDX S&P CNX Nifty index options are based on the popular market benchmarks S&P CNX Nifty index. Nifty index consist of 50 highly traded stocks and the representation of all industries. The instrument type is OPTIDX and the underlying asset is Nifty. S&P CNX Nifty index options contracts have three consecutive monthly contracts, additionally, three quarterly month of the cycle March/ June/September/December and five following semi-annual months of the cycle January/December. So that at any point in time there would be options contracts with at least 3 years tenure available. On expiration of the near month contract new contracts (monthly/quarterly/half yearly) are introduced at new strikes for both call and put options on the trading day following the expiry of the near month contract. Nifty options contracts expire on the last Thursday of the expiry month. If the last Thursday is a trading holiday, the contracts expire on the previous trading day.

Theoretical prices are calculated by using the BSOPM: The Black and Scholes model for option pricing gives the price of a call and put option as follows:-

$$c = SN(d_1) - Xe^{-r(T-t)}N(d_2)$$
$$p = Xe^{-r(T-t)}N(-d_2) - SN(-d_1) \qquad (1)$$

Where

$$d_1 = \{ln(S/X) + (r + \sigma^2/2)(T-t)\}/\sigma(T-t)^{1/2}$$
$$d_2 = d_1 - \sigma(T-t)^{1/2}$$

The variables are:-S = Index[2] price; X = strike price; (T – t) = time remaining until expiration, expressed as a percent of a year; r = current continuously compounded

2 CNX Nifty index is net of the present value of promised dividend.

risk-free interest rate (MIBOR).σ = annual volatility of stock price (the standard deviation of the short-term returns over one year); ln = natural logarithm; N(x) = standard normal cumulative distribution function; e = 2.718282. Implied volatility is inverted from the BSOPM under the assumptions that Indian options market is efficient and the options pricing model is valid for options on equity index.

The sampling procedure has been used and different as comparing to the previous study on Indian context. For any options (call/put) to be included in the sample it should be:(a)Traded on business day close to but after on expiry date, and have expiration on the next expiry date. (b) Close to at-the-money i.e. (S_t/X_t) Є (0.95, 1.05) where S_t is the index level and X_t is the strike price of the option. (c)Traded actively i.e. have relatively high trading volume. Here criterion (a) was used to avoid the overlapping of data. S&P CNX Nifty index options of NSE are of European style they are expiring on the last Thursday of the month. Every month three contracts are introduced near month, two month, and far month, for the present study only near month (one month) contracts are taken into account for sampling purpose. Therefore every year there will be 12 non-overlapping samples for call and put options. Criterion (b) was used because the option pricing model for calculating implied volatility was more accurate for close to ATM options. Thus, implied volatility obtained from these options may result into less measurement errors. ATM options may have been thinly traded and their prices would not necessarily reflect market price, thus Criterion (c) was required. By taking into account the above three criterion sampling is done for the S&P CNX Nifty index options for the period June, 2001 to May, 2011.

Let t be the business day that immediately follows an expiry date. On day t , the closing prices of $(C_t$ *and* $P_t)$ and strikes $(X_{t,c}$ *and* $X_{t,p})$ were recorded for a call option and put option, each of which expired on the next expiry date $t + 1$ and had highest trading volume among the close to ATM options. The corresponding underlying index level S_t was also recorded and one month *Mumbai Inter Bank Offered Rate* (MIBOR) from NSE debt segment download as the proxy of risk free rate of interest. The sampling process repeated upto 120 monthly observation for each call and put options.

Variable definition

In this section variable definitions and practical issues are discussed:

Time to Maturity (T –t): In practice, the time for paying interest is based on calendar days while the time for the life of an options is based on trading days. In this study the life of an option was about one month ranging from 27 to 34 days (about 18 to 23 trading days). For the present study one month MIBOR is taken as risk free rate of interest. Here, (T – t) indicates days to expiration was measured by number of days from the t business day and the day immediately prior to expiry day divided by the number of calendar days per year, that was taken as 365 i.e. (T – t) / 365. In this study the expiry day is not taken into account because all contracts expire on the day of expiration and the cash settled.

Implied volatility ($\sigma_{CIV,\ t}$ *and* $\sigma_{PIV,\ t}$) : Implied volatility is a transformation of a standard European option price. It is the volatility that, when input into the BSOPM formula, yields the price of the option. In other words, it is the constant volatility of the underlying process that is implicit in the price of the option. For this reason some authors refer to implied volatility as implicit volatility. Implied volatility is an alternative way to estimate volatility to be inferred from the options market, i.e. the current volatility of a stock as reflected by its option price. In other words, take the market price of the option, then invert the option pricing formula to determine the volatility implied by the traders in the market. For computing implied volatility commonly BSOPM model is used. Options pricing models cannot be inverted very easily, so implied volatility is calculated numerically. There are number of methods available for options pricing. Implied volatility estimated using BSOPM with method of Bisection as below.

$$\text{Volatility estimate} = \sigma_L + \frac{C - C_L}{C_H - C_L}(\sigma_H - \sigma_L) \quad (2)$$

Where σ_L and σ_H are the low and high volatility values, C_L and C_H are the corresponding options values and C is the market price of the options

Average implied volatility: ($\sigma_{AVRIV\,i,\ t}$) to use the all the months in the present data set, the new implied volatility measures are constructed (Hansen, 2001) as average of both the call and put implied volatility $\sigma_{AVRIV\,1,\ t}$, $\sigma_{AVRIV\,2,\ t}$, and $\sigma_{AVRIV\,3,\ t}$ defined as follows: [i = 1, 2, 3]

$$\sigma_{\text{AVRIV}1,\ t} = \sqrt{\frac{1}{2}\sigma^2_{c,t} + \frac{1}{2}\sigma^2_{p,t}} \quad (3)$$

$$\sigma_{\text{AVRIV}\,2,\ t} = \frac{1}{2}\sigma_{c,t} + \frac{1}{2}\sigma_{p,t} \quad (4)$$

$$\sigma_{\text{AVRIV}\,3,\ t} = \exp\{(\frac{1}{2}\ln\sigma_{c,t}) + (\frac{1}{2}\ln\sigma_{p,t})\} \quad (5)$$

Where, the implied volatility measures $\sigma_{\text{AVRIV}\,1,\ t}$ is constructed so that $\sigma^2_{AVRIV1,\ t}$ is the average of the implied variances, while $\sigma_{AVRIV\,2,\ t}$ is an average of the implied volatilities. The third measure is obtained by averaging the natural logarithm of the implied volatilities. For empirical estimation only Equation (5) is taken into account.

Realized volatility: ($\sigma_{RV,\ t}$): Shu and Zhang (2003) suggested that by constructing more suitable measure of realized volatility, the predictive power of implied volatility can be improved and also minimized the measurement error. Realized volatility is calculated as the standard deviation of the daily index return during the remaining life of the option, the period covered by the implied volatility. Since it is assumed that spot prices are log normally distributed, returns have been calculated according to their log ratios in prices and are therefore continuously compounded. Let n be the number of trading days before the expiration of an option, S_i be the index level, and R_i be the log –return on the i^th^ day during the remaining life of the option. Then realized volatility defined as follows :

$$R_i = \ln (S_i/S_{i-1}) \text{ where } i = 1,2,3,....n$$

$$\sigma_{RV,t} = \sqrt{\frac{252}{n-1}\sum_{i=1}^{n}(R_{i,t} - \overline{R}_t)} \tag{6}$$

$$\text{where } \overline{R}_t = \frac{\sum_{i=1}^{n} R_i}{n}$$

[Denotes the mean of daily log return of the index at time t]

Historical volatility: ($\sigma_{HV,\ t-1}$) In previous studies, historical volatility at time t was taken often defined as realized volatility at time t-1. In this study, the time to maturity ranged from 27 to 34 days (about 18 to 23 trading days). If the measurement followed as above, the information contained in the gap between two consecutive contracts would have been ignored (Hansen, 2001). It is often held that more recent data contains more relevant information about the future. Thus for the present study different definition of historical volatility is used as followed by (Hansen, 2001; Christensen and Hansen, 2002 and Li and Yang, 2009) for a given contract with T days to maturity at time t. the corresponding historical volatility was calculated by using the daily return of the period going back T days from time t. Then historical volatility defined as follows:

$$\sigma_{HV,t-1} = \sqrt{\frac{252}{T-1}\sum_{t=1}^{T}(R_{i,t-1} - \overline{R}_{t-1})} \tag{7}$$

$$\text{where } \overline{R}_{t-1} = \frac{\sum_{t=1}^{T} R_i}{T}$$

[Denotes the mean of daily log return of the index at time t-1]

Methodology and empirical results

In this section we develop an empirical model to determine the direction of causality using Granger models. In particular, a non-parametric test is also performed to check the market efficiency of S&P CNX Nifty index options.

Descriptive Statistics

Table 1 shows the descriptive statistics for multivariate time series data. It can be seen clearly that the average realized volatility ($\sigma_{RV,\,t}\ \sigma_{HV,\,t\text{-}1}$) they are smaller than the average put implied volatility ($\sigma_{PIV,\ t}$) , the same is found in case of (Panda et al. 2008; Hansen, 2001; Li and Yang, 2009). It may be due to implementation of portfolio insurance as suggested by Harvey and Whaley (1991). But by looking at the call implied volatility ($\sigma_{CIV\,,\,t}$) it is less than the all realized volatility that indicate investors least prefer the call index options for their portfolio insurance pertaining to the Indian derivative market. There is no significant difference between all other three averages implied volatility measures, they are found to be higher than all realized volatility.

Table 1 Descriptive statistics

Statistic(%)	$\sigma_{CIV,\,t}$	$\sigma_{PIV,t}$	$\sigma_{RV,t}$	$\sigma_{HV,\,t-1}$	$\sigma_{AVRIV\ 1,t}$	$\sigma_{AVRIV\ 2,t}$	$\sigma_{AVRIV\ 3,t}$
Mean	21	28	23	23	25	24	24
Maximum	66	78	72	77	73	72	72
Minimum	5	10	9	8	10	10	9
Std. Dev.	9	10	13	13	9	9	10

The maximum (minimum) value of put implied volatility is 78% (10%) while for call the value is 66% (5%). On the comparison of standard deviation reported in the fourth line for all volatility series; both realized volatility series are found to be more volatile as comparing to all other *ex –ante* volatility series. But, as per the assumption of BSOPM the annualized standard deviation should be constant.

Non-parametric test for market efficiency

To test the market efficiency of OPTIDX (options on index) index options as the predictor of future realized return volatility, a non-parametric test mechanism applied in the following way. Wilcoxon signed rank test is the non-parametric paired data testing procedure. Testing the null hypothesis that the median scores of the two time series population is same. For this reason, this test is applied in two ways: (1) if the market is efficient then; the pairs of non-overlapping at-the-money monthly implied volatility and realized volatility should be same. (2) Under the assumption of constant volatility of BSOPM call and put implied volatility should be same. Violation of this assumption violates the put-call parity theorem for option pricing model. In BSOPM annualized volatility is used to price both call and put

options, therefore implied volatility obtained from market price of call and put options should be same.
To test the above two hypothesis Wilcoxon W-statistic is calculated as follows: The Wilcoxon test statistic W is the sum of the all positive ranks.

$$W - stat = \sum_{i=1}^{T} R_i^{(+)} \tag{8}$$

E(W-statistic) = μ_W = T(T+1)/4 (9)
Var(W- statistic)= σ^2_W =T(T+1)(2T+1)/24 (10)
Standardized Z-test statistic defined as

$$Z = \frac{W - \mu_W}{\sqrt{\sigma_W{}^2}} \tag{11}$$

The critical valued of Z at 1% ,5% and 10% level of significance are respectively 2.58, 1.96 and 1.64.

In Table 2 variant of null tested using Wilcoxon signed rank test. In Table 2 first two lines shows the test of significance of market efficiency of OPTIDX CNX Nifty Index options. If the options market is efficient and BSOPM good holds then all the call and put implied volatility should conform to the realized volatility. It is seen clearly from Table 2, first line null is accepted, as the p-value is not significant. It signifies that call implied volatility best subsumes the information regarding future realized return volatility. However, at the same time put implied volatility does not conform to the realized volatility. It indicates that put implied volatility does not contain any information about future volatility. A test shown in the third line is the test of superiority of historical volatility against implied volatility as the best predictor of future volatility. It is seen that test statistic is insignificant, therefore, historical volatility subsume the information about the future realized volatility. At the same time, it raises the question regarding the market efficiency of OPTIDX market and applicability of BSOPM.
In the fourth line of Table 2, as per BSOPM an annualized volatility is used to price both the call and put options, therefore call and put implied volatility obtained from call and put price of options should be same. But it is seen from the test null is not accepted, call and put implied volatility are not identical. This is the violation of assumption of BSOPM. This indicates the possibility of mispricing of options (Varma, 2002) in the Indian derivative market. In Table 2 last line is the test of average implied volatility against realized volatility that also found to be significant, we cannot accept the null that average implied volatility is the best estimate of future volatility. To obtain more robust result on the market efficiency we employ the OLS and Granger Causality method as follows.

Table 2 Wilcoxon signed rank test

Null	W-statistic	Z
Ho: Median difference between log realized volatility and log call implied volatility is same.	W+ =3972	0.894
Null	W-statistic	Z
Ha: Median difference between log realized volatility and log call implied volatility is not same.	W- = 3288	(0.371)
Ho: Median difference between log realized volatility and log put implied volatility is same.	W+ = 1190	-6.388
Ha: Median difference between log realized volatility and log put implied volatility is not same	W- = 6070	(0.000)*
Ho: Median difference between log realized volatility and log historical implied volatility is same.	W+ = 3539	-0.237
Ha: Median difference between log realized volatility and log historical implied volatility is not same	W- = 3721	(0.812)
Ho: Median difference between log call implied volatility and log put implied volatility is same.	W+ = 116	-9.201
Ha: Median difference between log call implied volatility and log put implied volatility is not same	W- = 7144	(0.000)*
Ho: Median difference between log realized volatility and log average implied volatility is same.	W+ = 1991	-4.291
Ha: Median difference between log realized volatility and log average implied volatility is not same	W- = 5269	(0.000)*

*1%, ** 5% and ***10% Significant, Note: value in the square bracket shows the p-value.

Simple OLS estimation

This estimation gives the elementary results on the market efficiency of implied volatility as the best forecast of the future realized return volatility. This is based on the traditional measures call and put implied volatility. The following specification has been used for the OLS estimation:

$$\sigma RV,t = \alpha_0 + \alpha_c \sigma_{CIV,t} + \alpha_p \sigma_{PIV,t} + \alpha_{HV} \sigma_{HV,t-1} + e_t \quad (12)$$

Similarly,

$$\sigma RV,t = \alpha_0 + \alpha_c \sigma_{CIV,t} + \alpha_i \sigma_{AVRIV,t} + e_t \quad (13)$$

Table 3 OLS estimation

Dependent	Independent variable				Other Stat		Test of Residual		
Variable	Intercept	lnσCIV,t	lnσPIV, t	lnσHV,t-1		F-stat	LM-test	JB-stat	White test
lnσRV,t	-0.466	0.675							
	[-3.537]*	[8.63]*			0.38	74.58*	0.61#	9.86*	1.53
	{0.001}	{0.000}				{0.000}	{0.826}	{0.007}	{0.46}
lnσRV,t	-0.462		0.822						
	[-3.471*		[8.582]*		0.38	73.66	0.915#	13.19*	12.23*
	{0.000}		{0.000}			{0.000}	{0.535}	{0.001}	{0.00}
lnσRV,t	-0.723			0.535					
	[-5.835]*			[7.105]*	0.29	50.49*	1.211#	14.52*	0.249
	{0.000}			{0.000}		{0.000)	{0.285}	{0.000}	{0.88}
lnσRV,t	-0.415	0.516		0.197					
	[-3.119]*	[4.526]*		[1.939]***	0.40	40.04*	0.458#	12.42*	2.646
	{0.002}	{0.000}		{0.055}		{0.000}	{0.935}	{0.002}	{0.75}
lnσRV,t	-0.437		0.654	0.159					
	[-3.272]*		[4.285]*	[1.412]	0.38	38.14*	0.770#	14.14*	14.99
	{0.001}		{0.000}	{0.160}		{0.000)	{0.679}	{0.000}	{0.01}
lnσRV,t	-0.326	0.363	0.411	0.061					
	[-2.409]**	[2.857]*	[2.401]*	[0.529]	0.42	29.70*	0.602#	14.27*	17.45
	{0.017}	{0.005}	{0.017}	{0.597}		{0.000}	{0.836}	{0.000}	{0.04}
lnσRV,t	-0.328	0.384	0.456		0.43	44.69*	0.616#	13.84*	14.32
	[-2.436]**	[3.172]*	[3.075]*			{0.000}	{0.824}	{0.001}	{0.013}
	{0.016}	{0.002}	{0.002}						

[Table 3 shows OLS results of implied, historical and realized volatility based non-overlapping monthly at-the-money samples. LM-stat Ho: "No Serial Correlation" is obtained using Breusch-Godfrey Serial Correlation LM Test follows X2(12)distribution. JB-stat Ho: "Residuals are normally distributed" follows X2(2) distribution. White-stat Ho: " No Heteroskedasticity" using white test that also follows X2distribution. A value shown in the square bracket shows the t –statistic and corresponding p-value is shown in curly bracket. *1%, **5%, ***10%, Significant]

It is seen from the first line of the Table 3, the coefficient of call implied volatility for log-transformed series 0.675 and it is statistically significant, thus call implied volatility does contain information about the realized volatility. This primary result provides strong base for the options market efficiency and information content of implied volatility for the OPTIDX S&P CNX Nifty index option and also supports the past literature (Christensen and Prabhala, 1998, Hansen, 2001 and Li and Yang, 2009). But, as per hypothesis that $\alpha_o = 0$ and $\alpha_c = 1$, this results are different from it. The slope of call implied volatility is less than unity and the intercept is different from zero this indicates that call implied volatility is a biased estimator of future realized return volatility.

It is of inquisitiveness to know the predictive power of put implied volatility;

therefore univariate regression is performed in the second line of Table 3. For log-transformed value of put implied volatility slope coefficient found to be 0.822 and statistically significant. While comparing the two slope coefficient of call and put implied volatility, the coefficient of put implied is greater than the call implied volatility, this signifies that for Nifty Index option put implied volatility is the best forecast of the future volatility than call implied volatility. Put implied volatility is a biased estimate of future *ex-post* realized volatility because of the slope is less than one and intercept is non-zero.

By estimating a univariate regression with historical volatility as shown in third line of Table 3 it is analyzed that the slope coefficient for log-transformed series is 0.535 and found to be statistically significant. Historical volatility appears to contain additional information about the future realized return volatility, at the same time as intercept is not zero and significant. It signifies that historical volatility is biased estimate of subsequent realized volatility. But while comparing the explanatory power of call/put implied volatility with historical volatility it is too low 0.29 as in case of first two regressions adjusted R^2 reported in Table 3. The possible reason for additional information content of historical volatility may be the fact that historical volatility does contain more information beyond that in call/put implied volatility. One more contradictory conclusion come out that it violates the joint hypothesis of market efficiency and applicability of BSOPM.

It is essential to compare the call implied volatility with historical volatility; therefore some more regression shown in the fourth line of Table 3. In multiple regression the slope coefficient of call and historical volatility for log-transformed series is estimated respectively 0.516 and 0.197 and found to be statistically significant, still call implied volatility is more powerful than historical volatility as a predictor of future realized volatility. For univariate regression the adjusted R^2 was 0.38 while including historical volatility as an additional regressor adjusted R^2 increases 0.40, this signifies that for multiple regression; model remain less miss-specified and there is no problem of autocorrelation and heteroskedasticity. By estimating a regression of put implied volatility with historical volatility, the coefficient of log-transformed series found to be respectively 0.654 and 0.159 and statistically significant. In this multiple regression put implied volatility appears significant as the forecast realized volatility while historical volatility found to be insignificant. This indicates that put implied volatility does contain more information what already contained in the historical volatility. In the sixth line of Table 3 multiple regressions by taking call/put and historical volatility together as regressors. The slope of these three regressors found to be respectively 0.363, 0.411 and 0.061. In this regression call and put implied volatility appears to be positive significant as best forecast of future realized volatility. One interesting fact is that historical volatility does not appear significantly, that signifies historical volatility does not contain additional information what already contained in the options price.

One more interesting outcome of the study is that the Indian options market are efficient and call and put implied volatility are the best estimate of future volatility. By estimating a one more regression only with call and put implied volatility (reported in the last line of Table 3). The slope found to be respectively 0.384 and 0.455 still put implied volatility dominates the call implied volatility as a predictor of future realized volatility. For the present study it is strongly suggested for the Indian OPTIDX S&P CNX Nifty index options market is an efficient market and historical volatility does not subsume any information about future volatility what already contained in the implied volatility[3].

Granger Causality

Testing for the causality between two variables implies the specification of the dynamic relationship which links them. The test of causality between two economic variables it was proposed by Granger (1969) and extended by Sims (1972). This test is useful in determining a variable *y* can help in predicting another variable. If it cannot, then we say that y does not caused *x* and vice versa. One application of ad-hoc distributed lag models is to test the direction of causality in economic relationship. Such a test is useful when we know that two variables are related but we don't know which variable causes the other to move. Granger causality is a circumstance in which one time series variable consistently and predictably changes before another variable does (Granger, 1969). If one variable "causes" the other to change but we can be fairly sure that the opposite is not the case. Granger causality is important because it allows us to analyze which variable precedes or leads the other and such leading variables are extremely useful for forecasting purposes. Therefore, Granger causality allows us to prove economic causality in any rigorous way. The most commonly used Granger causality test are Granger (1969), Sims (1972) and Geweke . (1983) is discussed below[4]:

Granger Direct Causality Method

As the name implies Granger Causality is performed by taking lagged values of regressor and lagged value of dependent variable:

$$\sigma_{RV,t} = \alpha_1 + \sum_{i=1}^{p} \beta_i \sigma_{RV,t-i} + \sum_{j=1}^{q} \gamma_j \sigma_{IV,t-j} + u_t \tag{13}$$

$$\sigma_{IV,t} = \alpha_1 + \sum_{i=1}^{p} \beta_i \sigma_{IV,t-i} + \sum_{j=1}^{q} \gamma_j \sigma_{RV,t-j} + u_t \tag{14}$$

To estimate Equation (14) & (15) for the given lag length n is estimated using OLS

3 The results on combined implied volatility are identical with previous regressions.

4 For more detailed methodological recent application of Granger causality see Nair (2012) and Aslan, (2012).

and F-test performed to test the null $\gamma_j=0$

$$F-stat=\frac{(RRSS-URSS)/q}{URSS/(T-2q-1)} \tag{15}$$

Where URSS stand for Unrestricted Residuals Sum of Squares due to equation (14) & (15) and RRSS stand for Restricted Residuals Sum of Squares due to restriction on $\gamma_j=0$. *T* is the size of sample and *q* is the lag length of $\sigma_{IV,t-i}$ and *p* is the lag length of $\sigma_{RV,t-i}$ (*p* & *q* are the leg length). If *F-stat* is greater than critical value then for both the Equation (14) & (15) , then $\sigma_{IV,\ t-1} => \sigma_{RV,t} => \sigma_{IV,t-i}$ (i.e. $\sigma_{IV,t-i} <=> \sigma_{RV,t}$).

Granger Causality Sims Method

Sims model for causality is based on the past and future values of the regressor.

$$\sigma_{RV,t}=\alpha_3+\sum_{i=0}^{m}\lambda_i\sigma_{IV,t-i}+\sum_{j=1}^{n}\delta_j\sigma_{IV,t+j}+u'_t$$

$$\sigma_{IV,t}=\alpha_4+\sum_{i=0}^{m}\lambda_i\sigma_{RV,t-i}+\sum_{j=1}^{n}\delta_j\sigma_{RV,t+j}+u'_t \tag{17)(18}$$

According to Sims causality model only current and future values of regressor can cause the dependent variable. Here null $\delta_j=0$ is tested using F-statistic. The past literatures on empirical study of Sims model suggest that residual in the model are highly autocorrelated. The Geweke et.al. model (1983) is one of the modifications of Sims model for the correction of autocorrelation by taking lagged value of dependent variable.

Granger Causality Geweke et.al Method

$$\sigma_{RV,t}=\alpha_5+\sum_{i=1}^{u}\pi_i\sigma_{RV,t-i}+\sum_{k=0}^{v}\xi_i\sigma_{IV,t-k}+\sum_{j=1}^{w}\theta_j\sigma_{IV,t+j}+u''_t$$

$$\sigma_{IV,t}=\alpha_6+\sum_{i=1}^{u}\pi_i\sigma_{IV,t-i}+\sum_{k=0}^{v}\xi_i\sigma_{RV,t-k}+\sum_{j=1}^{w}\theta_j\sigma_{RV,t+j}+u''_t \tag{19)(20}$$

The null is tested for $\theta_j=0$ for $\sigma_{IV,t} \neq=> \sigma_{RV,t}$ against $\sigma_{IV,t} => \sigma_{RV,t}$ and vice versa. In Geweke model when lagged dependent variable included as regeressor it leads to fall in degrees of freedom and possible misspecification.

Before testing for the causality optimal number of lags should be estimated. Here optimal number of lag suggested is one using AIC and SBIC criterion[5].

The empirical results on Granger causality are described in Table 4 and 5. An attempt is made to tests the causality relationship between implied and realized volatility. Time series variable under Causality analysis are call implied volatility,

5 Due to space constraint results of Lag selection has been not reported here, results can be available on request.

put implied volatility, and average implied volatility (combined call and put implied volatility), realized volatility and historical volatility. The main reason behind doing Causality test is to analyze the direction of causality among the *ex –ante* and *ex –post* volatility.

For Causality test various models are specified (Equation 14-15, 17-18 and 19-20) and estimated using OLS regression. Estimated residuals are tested for autocorrelation, normality and heteroskedasticity. It is found that there are no significant problem of autocorrelation and heteroskedasticity. Therefore, the coefficient estimated for various models are consistent and efficient. However, in Sims model there is a problem of autocorrelation, therefore, Geweke model is adopted.

Table 4 Ganger causality using Granger Model

Null Hypothesis	F-Statistic	Q-Stat	Diagnostic Test of Residual			Inference
			LM-stat	JB-stat	White-stat	
CIV does not Granger Causes RV	4.66**	12.23	14.89	11.68	2.72	
	[0.033]	[0.427]	[0.247]	[0.003]	[0.743]	CIV
RV does not Granger Causes CIV	46.31*	8.18	8.27	259.00	3.59	RV
	[0.000]	[0.771]	[0.764]	[0.000]	[0.609]	
PIV does not Granger Causes RV	3.16***	10.44	13.16	12.43	2.94	
	[0.078]	[0.577]	[0.358]	[0.002]	[0.709]	PIV
RV does not Granger Causes PIV	70.28*	20.08	17.56	2.14	12.76	RV
	[0.000]	[0.066]	[0.129]	[0.343]	[0.026]	
AVRIV does not Granger Causes RV	4.85**	11.76	13.97	12.18	4.04	
	[0.030]	[0.465]	[0.0303]	[0.002]	[0.543]	AVRIV
RV does not Granger Causes AVRIV	75.61*	20.10	18.57	0.03	17.04	RV
	[0.000]	[0.065]	[0.010]	[0.985]	[0.004]	
HV does not Granger Causes RV	2.38	10.60	10.80	12.54	2.52	HV
	[0.125]	[0.563]	[0.546]	[0.002]	[0.774]	RV
RV does not Granger Causes HV	3443.17*	9.99	11.35	44.77	4.32	RV
	[0.000]	[0.616]	[0.499]	[0.000]	[0.505]	HV
PIV does not Granger Causes CIV	10.37*	8.67	12.94	149.12	14.24	PIV
	[0.002]	[0.731]	[0.374]	[0.000]	[0.014]	CIV
CIV does not Granger Causes PIV	2.76	16.56	18.20	29.98	11.41	CIV
	[0.099]	[0.167]	[0.109]	[0.000]	[0.043]	PIV

Null Hypothesis	F-Statistic	Q-Stat	Diagnostic Test of Residual			Inference
			LM-stat	JB-stat	White-stat	
HV does not Granger Causes CIV	2.04	10.37	11.54	142.13	1.96	HV
	[0.155]	[0.584]	[0.483]	[0.000]	[0.854]	CIV
CIV does not Granger Causes HV	17.67*	5.44	6.3	15.28	2.50	CIV
	[0.000]	[0.942]	[0.900]	[0.000]	[0.776]	HV
HV does not Granger Causes PIV	0.08	16.36	17.47	35.76	15.53	HV
	[0.772]	[0.175]	[0.133]	[0.000]	[0.008]	PIV
PIV does not Granger Causes HV	16.91*	9.38	9.02	34.15	13.80	PIV
	[0.000]	[0.670]	[0.701]	[0.000]	[0.017]	HV
HV does not Granger Causes AVRIV	0.42	21.73	22.30	27.85	7.65	HV
	[0.159]	[0.041]	[0.034]	[0.000]	[0.176]	AVRIV
AVRIV does not Granger Causes HV	24.59*	8.81	8.03	35.49	8.40	AVRIV
	[0.000]	[0.719]	[0.782]	[0.000]	[0.135]	HV

[Table 4 reports results on Ganger causality using Granger Model. F-stat Ho :___"Does Not Granger Causes"____, .The Values in square bracket shows p-value Q-stat Ho: "Residuals are white Noise", is obtained using Box-Pierces test statistics follows X2(12) distribution. LM-stat Ho: "No Serial Correlation" is obtained using Breusch-Godfrey Serial Correlation LM Test follows X2(12)distribution. JB-stat Ho: "Residuals are normally distributed" follows X2(2) distribution. White-stat Ho: " No Heteroskedasticity" using white test that also follows X2distribution. Implies unidirectional causality; Implies does not causes; Implies bi-directional causality. {*1%, **5%,*** 10%, significant,}]

Table 5 Ganger causality using Geweke Model (Correcting for the Autocorrelation)

Null Hypothesis	F-Statistic	Q-Stat	Diagnostic Test of Residual			Inference
			LM-stat	JB-stat	White-stat	
CIV does not Granger Causes RV	42.62*	6.29	7.05	6.30	17.20	CIV
	[0.000]	[0.901]	[0.854	[0.043]	[0.245]	RV
RV does not Granger Causes CIV	0.33	9.08	10.33	280.07	6.89	RV
	[0.570]	[0.696]	[0.587]	[0.000]	[0.939]	CIV
PIV does not Granger Causes RV	75.52*	12.70	13.23	0.11	26.52	PIV
	[0.000]	[0.391]	[0.353]	[0.947]	[0.022]	RV
RV does not Granger Causes PIV	0.0009	19.26	14.68	15.80	34.14	RV
	[0.976]	[0.082]	[0.259]	[0.000]	[0.002]	PIV
AVRIV does not Granger Causes RV	82.24*	9.99	11.26	0.64	22.14	AVRIV
	[0.000]	[0.617]	[0.506]	[0.727]	[0.076]	RV

Null Hypothesis	F-Statistic	Q-Stat	Diagnostic Test of Residual			Inference
			LM-stat	JB-stat	White-stat	
RV does not Granger Causes AVRIV	0.08	24.12	25.66	9.64	34.23	RV
	[0.774]	[0.020]	[0.012]	[0.008]	[0.002]	AVRIV
PIV does not Granger Causes CIV	1.25	10.61	11.45	517.86	26.64	PIV
	[0.266]	[0.562]	[0.490]	[0.000]	[0.021]	CIV
CIV does not Granger Causes PIV	3.56	15.00	18.59	4.43	55.33	CIV
	[0.062]	[0.242]	[0.099]	[0.109]	[0.000]	PIV

[Table 5 reports results on Ganger causality using Geweke Model. F-stat Ho :___"Does Not Granger Causes"____, .The Values in square bracket shows p-value Q-stat Ho: "Residuals are white Noise", is obtained using Box-Pierces test statistics follows X2(12) distribution. LM-stat Ho: "No Serial Correlation" is obtained using Breusch-Godfrey Serial Correlation LM Test follows X2(12)distribution. JB-stat Ho: "Residuals are normally distributed" follows X2(2) distribution. White-stat Ho: " No Heteroskedasticity" using white test that also follows X2distribution. Implies unidirectional causality; Implies does not causes; Implies bi-directional causality. {*1%, **5%,*** 10%, significant,}]

In Table 4 results on Granger causality are reported using Grange (1969) model. A variant of null hypotheses are tested for the possible rejection based F-statistic. The first line of the Table 4 F-stat signifies that both null are rejected. This implies that call implied volatility Granger Causes the realized volatility. Similarly, realized volatility also Granger Causes call implied volatility, this indicates the bi-directional Causality between call implied volatility and realized volatility. The same is true for put implied volatility shown in the second line of the Table 4. Sims and Geweke Model (see Table 5) clearly analyze that call/put implied volatility can cause the realized volatility and realized volatility cannot cause the implied volatility. It is also confirmed for the average implied volatility and, found that there is only unidirectional causality hold between implied and realized volatility. Based on this uncomplicated result it is concluded that Indian options market is an efficient market and incorporates all the recent information in the option prices. An ex- ante volatility obtained from options pricing model is the efficient forecast of the future realized return volatility. This result also confirms to the other options market of the globe like CBOE, NYSE, OEX, ASX, ADEX etc. The Causality result on the combined measures of implied volatility is reported in the third line of the respective Causality tables. The result shows that average implied volatility Granger Causes the realized volatility and the nature of causality is unidirectional.

In this study two different measures of ex –post realized return volatility are calculated. It is clearly seen from the Granger Table 4 the null "HV does not Granger Causes CIV" is accepted; the same is true for put implied volatility as well as combined implied volatility. Therefore, Granger Causality test suggest that historical volatility cannot be the best estimate of the future realized return volatility. Call and put implied volatility are the measure of current market volatility and best subsumes the information about future volatility.

All Granger Causality result analyze that call and put implied volatility cannot cause to each other. It is because of the assumptions of constant volatility of the BSOPM. In option pricing model single annualized volatility is used to price both the call and put options. Therefore, volatility predicted from call and put price should be identical. Granger[6] and Geweke et.al Causality model (see Table 5) supports the hypothesis “PIV does not Granger Causes CIV” and “CIV does not Granger Causes PIV”.

Conclusion

This study deals with the market efficiency of the OPTIDX CNX Nifty Index options. Implied volatilities are calculated for at-the-money non-overlapping monthly call and put options. The empirical results show that Indian options market is an efficient market that subsumes all the important information about the future volatility. This is a more comprehensive study in the Indian context based on causality analysis and employed three different approaches for non-overlapping at-the-money implied volatilities. It is concluded that call/put implied volatilities are the best estimate of future realized return volatility. It is also analyzed from the OLS estimation that historical volatility does not contain any significant information about the realized volatility what already contained in the options price. Granger Causality test concludes that there is only unidirectional causality prevails between implied volatility and realized volatility. Implied volatility can only causes the realized volatility; realized volatility cannot cause the implied volatility. One of the important result obtained from Granger test that historical volatility cannot cause the realized volatility. Finally, it is concluded that Indian options market is an efficient market and the volatility estimates based on option pricing model are the best forecast of the future volatility. This study can be useful for the volatility traders in the pricing of derivative instruments and portfolio risk management.

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