Relationship between Implied and Realized Volatility of S&P CNX Nifty Index in India

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Abstract

Measures of volatility implied in option prices are widely believed to be the best available volatility forecasts. According to the efficient market hypothesis, since implied volatilities are calculated based upon today's pricing information, they contain the best information about the market. Therefore, implied volatilities are considered as the best representation of market expectations. Recently, Christensen and Prabhala (1998) found that implied volatility in "at-the-money" one month OEX call options on S&P 100 index is an unbiased and efficient forecast of ex-post realized index volatility after the 1987 stock market crash. In this paper, we examine the information content of call and put options on the S&P CNX Nifty index. We examine one month at-the-money call option from 4-June-2001 to 28-oct-2004. We find that implied volatility contains more information than past realized volatility. In other words the predictability of implied volatility is more than that of past realized volatility. In fact, implied volatility remains significant even in the multiple regressions where historical volatility is included. Thus, we find that it is an efficient albeit slightly biased estimator of realized return volatility.

Keywords: Implied Volatility, Realized Volatility, Two Stage Least Square

JEL Classification: C22, C53, G10

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1 - Introduction

The correct valuation of derivatives is of crucial importance for practitioners in any financial market. Volatility of returns is a key input in the valuation of options. For a sophisticated trader, options trading is volatility trading and the trader who has best volatility forecast is likely to be the most successful trader.

There are several methods to predict the future volatility. Some measures of volatility express the volatility of a time series using only realizations of that time series to date. These volatility measures are "backward-looking" in the sense that they rely on the history of prices. Unlike these historical measures, "Forward-looking" measures of volatility rely on current prices, which incorporate all available information about future prices. Alternatively stated, since these current prices are determined by the best and most up-to-date information, they reflect participant's expectations about future market conditions. Under a rational expectations assumption, the market uses all the information available to form its expectations about future volatility, and, hence, the market option price provides the market's true volatility estimate. Furthermore, if the market is efficient, the market's estimated, implied volatility is the best possible forecast given the currently available information, which means that all information necessary to explain future realized volatility generated by all other explanatory variables in the market information set should be subsumed in the implied volatility.

The objective of this study is to investigate the predictive power of implied volatility against the past realized volatility of S&P CNX Nifty[4] index option in India. We distinguish our study from previous work in two ways. Firstly, we consider volatility data, sampled over a longer period (42 month) of time, while previous studies cover a time

[4] The S&P CNX Nifty is the leading index for large companies on the National Stock Exchange of India. It consists of 50 companies representing 24 sectors of the economy, and representing approximately 77% of the traded value of all stocks on the National Stock Exchange of India.

period of 3 months only. This increases the statistical power and allows for evolution of efficiency of the market dealing with S&P CNX Nifty index options that were introduced in 2001. Secondly, we sample the implied volatility and realized volatility series at near month (one month) frequency. This enables construction of volatility series with non-overlapping data with exactly one implied and one realized volatility that covers each time period in the sample.

Rest of the paper is organized along the following lines. In section II, we discuss previous studies. Section III describes how volatility series are constructed and provides descriptive statistics for these series. Section IV describes the methodology used in this study. In Section V, we present the empirical results, and Section VI concludes our study.

2 - Literature Review

Early studies of the information content of ISDs (Implied Standard Deviations) show that implied volatility contains substantial information for future volatility. Latane and Rendleman (1976), Chiras and Manaster (1978), and Beckers (1981), for example, regress future volatility on the weighted implied volatility across a broad sample of Chicago Board Options Exchange (CBOE) stocks, and find that options contain volatility forecasts that are more accurate than historical measures. These studies were performed shortly after the 1973 beginning of the CBOE option market and, therefore, use a relative short time span and focus on cross sections rather than time series predictions. These papers essentially document that stocks with higher implied volatilities also have higher ex-post realized volatility.

Scott and Tucker (1989) report some predictive ability in ISDs (Implied Standard Deviations) measured from PHLX currency options, but their methodology does not allow formal tests of hypothesis. They use OLS (Ordinary Least Square) regression with 5 currencies, 3 maturities, and 13 different dates. Because of correlations across observations, the usual OLS standard errors are severely biased, thereby invalidating hypothesis test.

Day and Lewis (1992) analyze options on the S&P 100 index from 1983 to 1989, and find that the ISD (Implied Standard Deviation) contain significant information content for weekly volatility, although not necessarily higher than that of time series models. This approach, however, ignores the term structure of volatility since the return horizon is not matched with the life of the option. Lamoureux and Lastrapes (1993), who examine options on ten stocks with expirations from 1982 to 1984, conclude that implied volatility is biased and inefficient. Both of these studies use overlapping sample and additionally, are characterized by a 'maturity mismatch' problem. Lamoureux and Lastrapes (1993) examine one-day-ahead and Day and Lewis (1992) examine one-week-ahead predictive power of implied volatilities computed from options that have a much longer remaining life (up to 120 trading days in the former and 36 trading days in the later). Therefore, the results are hard to interpret.

Canina and Figlewski (1993) regress the volatility over the remaining contract life against the implied volatility of S&P 100 index options over 1983 to 1986. They report that ISDs (Implied Standard Deviations) contain little predictive power for future volatilities appear to be even worse than simple historical measures.

Empirical research conducted on currency options, on the other hand, in general concludes that the implied volatility on short maturity contracts performs better in forecasting future volatility and contains information that is not present in historical volatility. Jorion (1995) investigates the information content of implied volatility from currency options traded on the Chicago Mercantile Exchange. Jorion (1995) finds that statistical time series models are outperformed by the volatility implied in short-term options although implied volatility appear to be a biased forecast.

With the options traded on the 'over-the counter' market, Galati and Tsatasaronis (1996) also evaluate the predictive power of volatility implied in currency options and show that implied volatility of short-maturity options performs better in forecasting future volatility, although it is a biased estimator. For longer horizons they find that neither historical nor implied volatility provides a good forecast of future volatility.

Christensen and Prabhala (1998) also examine the predictive power of implied volatility on S&P 100 index options. In contrast to previous work, they find that implied volatility outperforms historical volatility in forecasting future volatility. They attribute the difference in their results from those of Canina and Figlewski to the use of longer time series and non-overlapping data. They also provide evidence that there is regime shift following the oct-1987 stock market crash, with implied volatility being more biased before the crash than after the crash.

Fleming (1998) examines the performance of the S&P 100 implied volatility as a forecast of future stock market volatility. The results indicate that the implied volatility is an upward biased forecast, but also that it contains relevant information regarding future volatility.

Kai (2002) compares the predictive ability of implied volatility and historical volatility for three major currencies. Kai shows that historical volatility at horizons ranging from one month to six months contains more information regarding future realized volatility.

Szakmary, Ors, and Kim (2003) use data from 35 futures options markets from eight separate exchanges and test for the predictive power of implied volatilities in the underlying futures market. They report that implied volatilities outperform historical volatility as a predictor of the realized volatility for a large majority of commodities included in their study.

Giot (2002) assesses the efficiency, information content and unbiasedness of volatility forecasts based on the VIX/VXN implied volatility indices, RiskMetrics and GARCH type models at the 5-, 10- and 22-day time horizon. His empirical application focuses on the S&P100 and NASDAQ100 indices. He also deals with the information content of the competing volatility forecasts in a market risk (VaR type) evaluation framework. The performance of the models is evaluated using LR, independence, conditional coverage, and density forecast tests. His results show that volatility forecasts based on the VIX/VXN indices have the highest information content, both in the volatility forecasting and market risk assessment frameworks. Because they are easy-to-use and compare very favorably with much more complex econometric models that use historical returns, he argues that options and futures exchanges should compute implied volatility indices and make these available to investors.

Claessen and Mittnik (2002) examine alternative strategies for predicting stock market volatility. Employing German DAX-index return data, they find that past returns do not contain useful information beyond the volatility expectations that is already reflected in option prices.

Becker, Clements and White (2006) examine whether a publicly available and commonly used implied volatility index, the VIX index (as published by the Chicago Board of Options Exchange) is in fact efficient with respect to a wide set of conditioning information. Results indicate that the VIX index is not efficient with respect to all the elements in the information set that may be used to form volatility forecasts

Pong, Shackleton, Taylor, and Xu (2004) find significant incremental information in historical forecasts beyond the implied volatility information to predict future realized volatility for forecasts horizons up to one week. Jiang and Tian (2005) use S&P 500 index options to compare the predictive ability of implied volatility and historical volatility. They conclude that implied volatility is a more efficient forecast for the future realized volatility.

3 - Data and Sampling Procedure

3.1 Data Description

We consider S&P CNX Nifty index options which started trading from June 4, 2001 under National Stock Exchange (NSE). The index consists of 50 highly traded scripts drawn from diverse industries and markets. The index options contracts have a maximum of 3 months trading cycle (1^{st} month-Near month, 2^{nd} month-middle month and, 3^{rd} month- Far month). New contracts are introduced on the trading day following the expiration of the near month contract. Exchange provides a minimum of seven strike prices for every option type (call and put) during the trading month. Our empirical analysis focuses on S&P CNX Nifty index options. We consider the daily closing price basis net of dividend of S&P CNX Nifty index and the index call option closing price with 17 trading days to expire (Near month) from 4^{th} July-2001 to 28^{th} Oct-2004 . The S&P CNX Nifty has been obtained from the CD-ROM provided by NSE and the NSE website (nseindia.com).

3.2 Sampling Procedure

By convention, S&P CNX Nifty options expire last Thursday of every month. The Friday that immediately follows the expiration, we record the S&P CNX Nifty index level, $S_{t.}$ If Friday is a holiday, then we consider the next business day. On the same date, we locate a call option that is expiring next month and is closest to being at-the-money. We record the price, C_t of this call as well as its strike price, K_t. This option expires on the last Thursday of the following month (t +1); the next (t + 1) call option is sampled on the Friday that immediately follows the expiration. An entire sequence of option prices is constructed in this manner. The key feature of this sampling procedure is to remove the non-overlapping problem.

4 – Methodology

4.1 Forward Looking Measure of Volatility

The implied volatility of an option is defined as the expected future volatility of the underlying asset over the remaining life of the option that equates the fair value of the option implied by a particular model to the option's actual market price. Many studies conclude that measures of option implied volatility are, indeed, the best predictor of future volatility.

Unlike time series measures of volatility that are entirely backward-looking, option implied volatility is "backed-out" of actual option prices –which, in turn, is based on actual transactions and expectations of market participants- and, therefore, is inherently forward-looking. This measurement incorporates the most current market information and, therefore, it should reflect market expectations better than the historical measure.[5]

In the Black-Scholes model, the one unobserved parameter is the volatility of the underlying stock. Theoretically, the proper volatility input in the Black-Scholes model is the instantaneous variance of asset returns, which means the variance of underlying asset's return over an infinitesimal time increment. Merton (1973)

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[5] See Fama (1971, 1990)

shows that under this interpretation, the volatility implied by the Black-Scholes model can be interpreted as the expected future instantaneous variance of the underlying asset's return over the remaining life of the option.[6]

To find out implied volatility of European call and put option with a given market price of the option, current stock price and interest rate, the value of volatility is derived by substituting those observed values into the Black-Schole model. The resulting value of σ is called the Black-Scholes implied volatility[7], because that number represents the volatility of the underlying asset that is implied by quoted option price and the Black-Scholes model.

In this study, we examine the relationship between volatility implied by an option price and subsequently realized index return volatility. We, therefore, construct a time series of realized volatility. 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 differences in prices and are, therefore, continuously compounded. Therefore, the following method has been used to calculate daily index return.

$$r_k = \ln S_k - \ln S_{k-1} \qquad (1)$$

Where, S_k denotes the spot price on day k. Let $\bar{r} = \frac{1}{T}\sum_{k=1}^{T} r_{t,k}$ denotes the sample mean of the index returns in month t. The annualized realized standard deviation for index return for the month t is given by:

$$R_t = \sqrt{\frac{1}{T}\sum_{k=1}^{T}(r_{t,k} - \bar{r}_t)^2} \qquad (2)$$

Where, k runs from Friday following the last Thursday in month t to the last Thursday in month (t + 1). Here, T denotes the number of

[6] see Merton(1973)
[7] Implied volatility for both call and put options

trading days to maturity of options with expiration in month (t + 1). While implied volatility is known at the beginning of period t, the realized volatility R_t is not known until the end of period t (the expiration day of option). Finally, the analysis is based on both volatility and log-volatility series, which we denote by CI_t as call implied volatility, PI_t as put implied volatility, LCI_t as log-call implied volatility, LPI_t as log-put implied volatility, R_t as realized volatility, and LR_t as log-realized volatility (the study considers log as natural logarithm) at time t.

Table 1 provides descriptive statistics for the three volatility series-- the implied volatility for S&P CNX Nifty index options and the realized index return volatility.

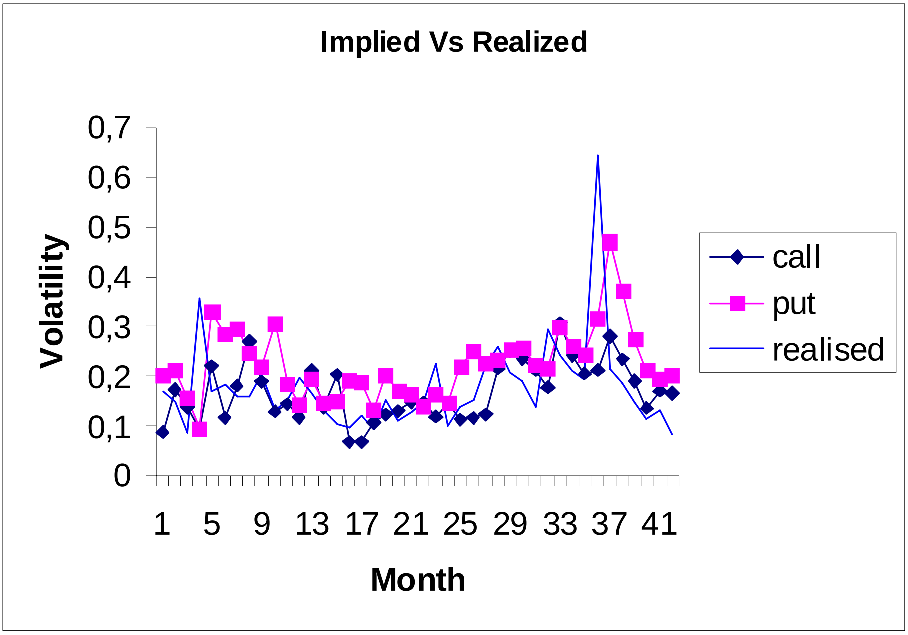
Table 1 **Descriptive Statistics for each of the six series used in this study**

Statistics	Call-Implied Volatility (CI_t)	Put-Implied Volatility (PI_t)	Realized Volatility (R_t)	Log- Call-Implied Volatility (LCI_t)	Log- Put-Implied Volatility (LPI_t)	Log-Realized Volatility (LR_t)
Mean	0.17	0.22	0.17	-1.83	-1.53	-1.80
Standard Deviation	0.058	0.071	0.093	0.36	0.30	0.38
Skewness	0.38	1.06	3.24	-0.33	0.009	1.00
Kurtosis	2.44	4.89	16.38	2.62	3.26	5.22
Jarque-Bera	1.58	14.28	386.14	1.03	0.124	15.66

On an average, the put implied volatility is slightly higher than the realized volatility and call implied volatility. This is consistent with Harvey and Whaley (1991, 1992) who suggest that it may be due to the fact that buying index puts is a convenient and relatively inexpensive way to implement portfolio insurance. This leads to an excess buying pressure on index puts to index calls, and, in turn, results in a high put implied volatility compared to those obtained from the corresponding calls. The data also shows an interesting pattern in the standard deviation of the volatility series. The implied volatilities are less volatile than realized volatility.

Both implied and realized volatility are highly skewed and leptokurtic, whereas the distribution of the log-volatility series are less skewed. The Jarque-Bera test of normality, JB, is significantly smaller for the log-transformed series, which indicates that the log-transformed series conform better to normality than the raw series. The three volatility time series are plotted in Figure 1.

Figure 1



5 - Empirical Results

In this section, we examine the relationship between realized return volatility and volatility implied by the option price. In the study both linear and log-linear relationships have been estimated, because the logarithm of volatilities conforms best to normality and it also enables us to compare our results with the previous literature.

The predictive ability of implied volatility is evaluated by regressing realized volatility (R_t) on the call implied volatility and the put implied volatility, respectively.

$$R_t = \alpha_0 + \alpha_c CI_t + \varepsilon_t \tag{3}$$

Where, R_t denotes the realized volatility for period t and CI_t denotes the call implied volatility and for put option analysis PI_t denotes the put implied volatility at the beginning of period t. While performing a regression using equation 3, we also consider LR_t (Log of Realized Volatility at time t), LCI_t (Log of Call Implied Volatility at time t), and LPI_t (Log of Put Implied Volatility at time t) in equation 3, instead of R_t, CI_t and PI_t, respectively.

Specifically, we test three hypotheses using equation 3. First, if call implied volatility contains some information about future volatility then α_c should be nonzero. Second, if call implied volatility is an unbiased forecast of realized volatility, then $\alpha_o = 0$ and $\alpha_c = 1$. Finally, if call implied volatility is efficient, the residuals ε_t should be white noise and uncorrelated with any variables in the market information set. The same methodology is used to evaluate the predictive ability of put implied volatility.

Before performing regression analysis, we test for unit root in all the series, because if volatility series possesses a unit root, regressions as specified above are spurious. Unit root test is carried out through Dickey-Fuller (DF), Augmented Dickey Fuller (ADF) and Phillips-Perron (PP) tests. The results of unit root test given in the Table 2 suggest that all the variables are stationary at 1-percent level.

Table 2 **Test of Stationarity for each of the six time series using Dickey-Fuller, Augmented Dickey-Fuller, and Philip-Perron methods.**

LEVELS						
Variables	Without Trend			With Trend		
	DF	ADF	PP	DF	ADF	PP
R_t	-5.22*	-3.42**(1)	-5.28*(3)	-5.27*	-3.43***(1)	-5.32*(3)
CI_t	-4.00*	-2.71***(1)	-4.03*(3)	-4.21*	-2.97	-4.27*(3)
PI_t	-3.24**	-2.91***(1)	-3.21**(3)	-3.39**	-3.12	-3.38***(3)
LR_t	-4.40*	-2.74***(1)	-4.41*(3)	-4.39*	-2.65	-4.50*(3)
LCI_t	-4.10*	-2.66***(1)	-4.16*(3)	-4.31*	-2.96	-4.39*(3)
LPI_t	-3.52**	-2.86***(1)	-3.50**(3)	-3.76**	-3.15	-3.77**(3)

Note: * Reject the null hypothesis of a unit root with 99% confidence
** Reject the null hypothesis of a unit root with 95% confidence
*** Reject the null hypothesis of a unit root with 90% confidence
Figures in the brackets against ADF statistics are the numbers of lags used to obtain white noise residuals, and these lags are selected using AIC.
In PP test we used the lag length 3. This optimal lag length is selected using the Newey-West method.
R_t is the realized volatility, CI_t as call implied volatility, PI_t as put implied volatility, LCI_tas log-call implied volatility, LPI_tas log-put implied volatility, and LR_t is the log-realized volatility.

Ordinary Least Square estimates of equation (3) for both volatility level series and log-volatility series are reported in Table 3.

Table 3 **Ordinary Least Square Estimation of Realized Volatility**

Note: *1% and **5% level of significance.

Here, CI_t and PI_t are denotes the Black-Scholes call implied volatility and put implied volatility for at-the-money options on S&P CNX Nifty index, measured at the beginning of month t, and R_t denotes the ex-post daily return volatility of the index, over the remaining life of the option. The regressions reported in the right side of each panel are of the logarithmic form. Where, LR_t, LCI_t, and LPI_t satisfy LR_t = log R_t, LCI_t = log CI_t, and LPI_t= log PI_t. The results reported in the table are based on nonoverlapping monthly volatility observations for the 42 months from 4-june-2001 to 28-oct-2004. Numbers in the parentheses denote asymptotic t statistics.

OLS Estimates Dependent Variable: Realized volatility (R_t)							OLS Estimates Dependent Variable: Log Realized volatility (LR_t)						
Independent Variables	Intercept	CI_t	PI_t	R_{t-1}	R^2	DW	Independent Variables	Intercept	LCI_t	LPI_t	LR_{t-1}	R^2	DW
Call Implied Volatility (CI_t)	0.11* (2.48)	0.42** (1.71)			0.06	2.03	Natural Log of Call Implied Volatility (LCI_t)	-1.16* (-3.86)	0.34* (2.14)			0.10	1.90
Put Implied Volatility (PI_t)	0.10* (2.08)		0.37** (1.83)		0.07	2.05	Natural Log of Put Implied Volatility (LPI_t)	-1.20* (-4.01)		0.40* (2.06)		0.09	1.89
Past Realized Volatility (R_{t-1})	0.15* (4.60)			0.16 (1.02)	0.02	2.01	Natural Log of Past Realized Volatility (LR_{t-1})	-1.27* (-4.37)			0.30** (1.87)	0.08	2.05
Call Implied Volatility (CI_t) and Past Realized Volatility (R_{t-1})	0.10* (2.27)	0.45 (1.33)		-0.02 (-0.08)	0.07	2.02	Natural Log of Call Implied Volatility (LCI_t) and Natural Log of Past Realized Volatility (LR_{t-1})	-1.08* (-3.31)	0.30 (1.23)		0.09 (0.41)	0.11	2.02
Put Implied Volatility (PI_t) and Past Realized Volatility (R_{t-1})	0.10** (1.89)		0.48 (1.52)	-0.12 (-.47)	0.08	1.92	Natural Log of Put Implied Volatility (LPI_t) and Natural Log of Past Realized Volatility (LR_{t-1})	-1.13* (-3.50)		0.27 (1.01)	0.13 (0.62)	0.10	1.98

Using only one independent variable, we observe that both the implied volatilities contain more information than past realized volatility. The slope coefficients for both call implied volatility and log-call implied volatility are 0.42 and 0.34 and these are statistically significant.

In the case of put option, the estimated value of slope coefficients for both put implied volatility and its log transformation are 0.37 and 0.40 and are statistically significant. The Durbin-Watson statistics (DW) are not significantly different from two for both the cases indicating that the residuals from the regression equations are not auto-correlated.

For the realized volatility in both the cases, value of slopes is too low and the respective t-statistics are insignificant. Hence, it can be concluded that implied volatility (both call and put) contains more information about future volatility than the realized volatility. However, it appears to be a biased forecast of future volatility since slope coefficient is different from unit and intercept is different from zero for both the cases (volatility and log-volatility).

Subsequently, we compare the information content in implied volatility to that of past realized volatility by estimating the following multiple regression for both volatility level and log-volatility series for call options and for the put options.

$$R_t = \alpha_0 + \alpha_0 CI_t + \alpha_h R_{t-1} + \varepsilon_t \tag{4}$$

OLS estimates of equation (4) are reported in Table 3. Past realized volatility in isolation explains future volatility, which is already discussed earlier in this paper. However, once call implied volatility is added as an explanatory variable, the regression coefficients for both past realized volatility and past log-realized volatility α_h drops from 0.16 to –0.01 and from 0.30 to 0.09, respectively. In the case of put options, the regression coefficients for both past realized volatility and past log-realized volatility α_h drops from 0.30 to 0.13, respectively, but the t-statistic is insignificant in the second case. Nevertheless, the slope coefficient for implied volatility itself remains significant in the multiple regressions and, in particular, is much more than the coefficient of past realized volatility.

Therefore, our results confirm that S&P CNX Nifty index option implied volatility is an efficient but a biased estimator of realized volatility. Nevertheless, implied volatility has more predictive power than the past realized volatility whether judged by magnitude of the regression slope coefficient or by R^2 for each regression discussed above. From the above findings we can conclude that the implied volatility contains information about future volatility beyond what is contained in the past realized volatility.

As shown first by Christensen and Prabhala (1998), there is a potential misspecification problem in interpreting the results of OLS encompassing regression presented in Table 3. The misspecification is driven by potential measurement error implicit in implied volatility. To overcome this difficulty, the present study implements a two-stage least square regression method. In the first stage, implied volatility on two instrumental variables, namely, lagged realized volatility and lagged implied volatility are regressed (Equation (5)).

As shown in Equation (6), we use fitted values of implied volatility as regression in the second stage. In these cases, for calls and puts, the two-stage least square method is also applied for their log transformation.

First stage,

$$CI_t = \alpha_0 + \alpha_c CI_{t-1} + \alpha_h R_{t-1} + \varepsilon_t \tag{5}$$

We examine this specification for at least two reasons. First, we use specification (5) in an instrumental variable framework to correct error in variable problems in call implied volatility. Second, we use it to test whether call implied volatility is predicted by past volatility. If option prices reflect volatility information, call implied volatility should not only predict future volatility, but should also endogenously depend on past volatility, since past and future volatility are positively related. We test this implication using regression equation (5).

Second stage,

$$R_t = \beta_0 + \beta_c CI_t + \varepsilon_t \tag{6}$$

In the contrast to previous studies [Christensen and Prabhala (1998); Christensen and Hansen (2002)], the present study does not include the lagged realized volatility separately in the second stage. The generated regressor used in the second regression is a linear combination of lagged realized volatility and lagged call implied volatility. If we include lagged realized volatility in a regression along with the generated regressor, it would result in a multicollinearity problem by construction. Similarly, Christensen and Hansen (2002)'s approach, in which both call and put regressors are specified together in the second stage regression, results in problem of multicollinearity. Therefore, our study analyzes call and put implied volatility separately.

The results of the first stage regression are presented in Table 4, while the second stage results are in Table 5.

Table 4 **Instrumental Variable Estimation (IV) method**

First stage Regression estimates for both call and put

Dependent variable (IC_t)					Dependent Variable (LIC_t)				
Intercept	IC_{t-1}	R_{t-1}	R^2	DW	Intercept	LIC_{t-1}	LR_{t-1}	R^2	DW
0.0571* (2.66)	0.30* (2.57)	0.35* (4.83)	0.50	2.10	-0.3509 (-1.52)	0.60* (5.60)	0.21** (1.98)	0.56	2.11
Dependent Variable (IP_t)					Dependent Variable (LIP_t)				
Intercept	IP_{t-1}	R_{t-1}	R^2	DW	Intercept	LIP_{t-1}	LR_{t-1}	R^2	DW
0.0451* (2.09)	0.40* (4.41)	0.50* (7.20)	0.71	2.09	-0.1599 (-0.813)	0.33* (2.99)	0.48* (5.36)	0.58	2.10

Note: *1% and **5% level of significance.

The results reported in the table are based on nonoverlapping monthly volatility observations for the 42 months from 4-June-2001 to 28-Oct-2004. Numbers in the brackets denote asymptotic t statistics.

Second stage of Instrumental Variable Estimates

<table>
<tr><td colspan="8">Analysis for Call option</td></tr>
<tr><td colspan="4">Dependent variable-R_t</td><td colspan="4">Dependent variable-LR_t</td></tr>
<tr><td colspan="4">Instrumental variable for IC_t – IC_{t-1}</td><td colspan="4">Instrumental variable for LIC_t – LIC_{t-1}</td></tr>
<tr><td>Intercept</td><td>IC_t</td><td>R^2</td><td>DW</td><td>Intercept</td><td>LIC_t</td><td>R^2</td><td>DW</td></tr>
<tr><td>0.0428
(0.4331)</td><td>0.80
(1.38)</td><td>0.02</td><td>2.15</td><td>-0.5182
(-0.7135)</td><td>0.70**
(1.78)</td><td>0.02</td><td>2.17</td></tr>
<tr><td colspan="4">Dependent variable-R_t</td><td colspan="4">Dependent variable-LR_t</td></tr>
<tr><td colspan="4">Instrumental variable for IC_t – IC_{t-1}, R_{t-1}</td><td colspan="4">Instrumental variable for LIC_t – LIC_{t-1}, LR_{t-1}</td></tr>
<tr><td>Intercept</td><td>IC_t</td><td>R^2</td><td>DW</td><td>Intercept</td><td>LIC_t</td><td>R^2</td><td>DW</td></tr>
<tr><td>0.0913
(1.46)</td><td>0.51
(1.44)</td><td>0.06</td><td>2.10</td><td>-0.9121*
(-2.18)</td><td>0.50*
(2.17)</td><td>0.10</td><td>2.05</td></tr>
<tr><td colspan="8">Analysis for Put option</td></tr>
<tr><td colspan="4">Dependent variable-R_t</td><td colspan="4">Dependent variable-LR_t</td></tr>
<tr><td colspan="4">Instrumental variable for IP_t – IP_{t-1}</td><td colspan="4">Instrumental variable for LIP_t – LIP_{t-1}</td></tr>
<tr><td>Intercept</td><td>IP_t</td><td>R^2</td><td>DW</td><td>Intercept</td><td>LIP_t</td><td>R^2</td><td>DW</td></tr>
<tr><td>0.1192
(1.48)</td><td>0.27
(0.7544)</td><td>0.07</td><td>1.95</td><td>-1.08**
(-1.87)</td><td>0.48
(1.25)</td><td>0.09</td><td>1.90</td></tr>
<tr><td colspan="4">Dependent variable-R_t</td><td colspan="4">Dependent variable-LR_t</td></tr>
<tr><td colspan="4">Instrumental variable for IP_t – IP_{t-1}, R_{t-1}</td><td colspan="4">Instrumental variable for LIP_t – LIP_{t-1}, LR_{t-1}</td></tr>
<tr><td>Intercept</td><td>IP_t</td><td>R^2</td><td>DW</td><td>Intercept</td><td>LIP_t</td><td>R^2</td><td>DW</td></tr>
<tr><td>0.1170*
(2.10)</td><td>0.28
(1.15)</td><td>0.07</td><td>1.96</td><td>-0.1031**
(-2.61)</td><td>0.51**
(1.99)</td><td>0.08</td><td>1.90</td></tr>
</table>

Note: *1% and **5% level of significance.
The results reported in the table are based on nonoverlapping monthly volatility observations for the 42 months from 4-June-2001 to 28-Oct-2004. Number in the brackets denotes asymptotic t statistics.

The first stage regression shows that both the explanatory variables are highly significant in the case of both call and put implied volatility. This signifies that the past realized volatility and past implied volatility (both call and put) impact implied volatility.

For the analysis of second stage regression, we divide Table 5 into two parts and each part is again divided into two sub parts. First part deals with the call option and second part deals with the put option and the sub parts deal with the selection of instrumental variables. In the first sub part we deal with lagged implied volatility as an instrumental variable. In the second sub part we deal with lagged implied and lagged realized as an instrumental variables for both call and put options. We use only the lagged implied volatility (for both call and put) as instrumental variables. If only lagged implied volatility is allowed as an instrument, then all the explanatory power ascribed to implied volatility in the estimation is based on information backed out of option prices. In order to analyze this issue, we repeat the instrumental variable procedure. When constructing the instrument, we use fitted values from implied volatility equation with lagged realized volatility excluded. The results appear in the first sub part of Table 5 for the call and put option. In the case of call option, the slope of the call implied volatilities are higher than the OLS regression for the level series, but they are not significant; the results are high and significant in the log transformation case. In the case of put option, the put implied volatilities are lower than the OLS regression for the level series and they are not significant, but they are high and significant in the log transformation case. Overall the slope coefficient of call implied volatility is slightly larger than put implied volatility. It also shows that the slope of the implied volatility is higher than the OLS estimation for both call and put option. Thus the results show that implied volatility contains information about the future volatility but it is a biased estimator.

6 – Conclusions

There are two major concepts applied for estimating future volatility—one is assessment from historical data, while the others are utilizing option pricing theory to get expected future volatility from option prices. This paper offers a critical look at the widely held belief that implied volatility computed from market options prices is an informationally efficient forecast of the volatility that will actually be experienced by the underlying asset from the present through the expiration date. Based on this background our study investigates whether the implied volatilities of S&P CNX Nifty call and put option predict the future realized index return volatility. For this analysis, we consider one month (near month) sampling frequency and nonoverlapping data for 42 months, so that exactly one implied volatility and realized volatility estimate pertain to each month. The study considers implied volatilities derived from Black-Scholes model of one-month at-the-money option on the S&P CNX Nifty index. As an extension we separate the analysis of the volatilities implied in put and call options. We show that implied put volatility on an average is slightly greater than implied call volatility, possibly because of buying put index options is a relatively cheaper and convenient way of implementing portfolio insurance. A unit root test of the call implied volatility, put implied volatility and realized volatility series suggests that all the variables are stationary at level.

The OLS results indicate that call implied volatility is a better forecast than put implied volatility. The study also uses an instrumental variable method to correct error in variable problems in call implied volatility and also to test whether call implied volatility is predicted by past volatility. From both OLS and instrumental variables methods, we find that past realized volatility does not add any information beyond what is already contained in the implied volatility. The results support the hypothesis that the implied volatility dominates historical volatility in forecasting realized volatility, or that all the information contained in historical volatility is being reflected by the implied volatility, and the historical volatility has no incremental forecast ability. Therefore, we cannot reject the hypothesis that the volatility implied by one month (near month) at-the-money call option price is efficient and, albeit, slightly biased estimator of realized return volatility. This biasness may be due to the fact that the implied volatility does not contain all the market information.

References

Black, F., and M. Scholes, 1973, The Pricing of Option and Corporate Liabilities, *Journal of Political Economy*, 81, 637-659

Beekers, S., 1981, Standard Deviations Implied in Options Prices as Predictors of Future Stock price Variability, *Journal of Banking and Finance*, 363-381

Becker, R., A.E Clements and S.I. White (2006), On the informational efficiency of S&P500 implied volatility, *North American Journal of Economics and Finance*, 17,139–153

Bollerslev, T. (1986), Generalized Autoregressive Conditional Heteroskedasticity, *Journal of Econometrics*, 31, 307-327

Canina, L. and S. Figlewski, (1993), The Information Content Implied Volatility, *Review of Financial Studies*, 6, 659-681

Chiras, D., and S. Manaster, 1978, The Information Content of Option Prices and a Test of Market Efficiency, *Journal of Financial Economics*, 10, 28-58

Christensen, B.J., and N.R. Prabhala, (1998), The Relation Between Implied and Realized volatility, *Journal of Financial Economics*, 50, 125-150

Christensen, B. J., and C. S. Hansen, (2002), *New Evidence on the Implied Volatility Relation*, 8, 187-205

Day, T., and C. Lewis, (1988), The Behaviour of the Volatility and the Information Content of Sock Index Option, *Journal of Financial Economics*, 52, 103-122

Day, T., and C. Lewis, (1992), Stock Market Volatility and Informational Content of Stock Index Option, *Journal of Econometrics*, 52, 267-287

Edey, M., and G. Elliott, (1992), Some Evidence On Option Prices As Predictors Of Volatility, *Oxford Bulletin of Economics and Statistics*, 54, 567-578

Fama, E. F. (1970), Efficient Capital Markets: A Review of Theory and Empirical Work, *Journal of Finance*, 25, 383-417

Fama, E. F, (1990), Efficient Capital Market: II, *Journal of Finance*, 46, 1575-1617

Fleming, J., (1998), The Quality of Market Volatility Forecasts Implied by S&P 100 Index Option Prices, *Journal of Empirical Finance* 5, 317-345.

Giot, P, (2002) The Information Content of Implied Volatility Indexes for Forecasting Volatility and Market Risk, December 13, *Working paper*.

Hansen, C. S., (1999), The Relationship Between Implied and Realized Volatility in the Danish Option and Equity Markets, *working paper*

Harvey, C. and Whaley, R. (1991), S&P index option volatility, *Journal of Finance*, 46, 1551-15561

Harvey, C. and Whaley, R. (1992), Market volatility prediction and the efficiency of the S&P 100 index option market, *Journal of Financial Economics*, 31,43-73

Hansen, C. S., (1999), The Relation between Implied and Realized Volatility in Danish Option and Equity Markets, *Working Paper*

Hull, J. C. (2003), *Options, Futures and Other Derivatives*, 2nd edition, Prentice Hall, Englewood, NJ.

Holger ,C. and Mittnik, S. (2002), *Forecasting stock market volatility and the informational efficiency of the DAX-index options market*, 8, 302-321.

Jorion, P., 1995, Predicting Volatility in the Foreign Exchange Market, *Journal of Finance*, 50, 507-528

Kuen, T. Y., and T. S. Hoog, Forecasting Volatility in the Singapore Stock Market, *Asia Pacific Journal of Management*, 9, 1-13

Latane, H., and R. Rendleman, (1976), Standard Deviation of Sock Price Ratios implied by option premia, *Journal of Finance*, 31, 369-382

Lamoureux, D., and W. Lastrapes, (1993), Forecasting Stock Return Variance: Toward an Understanding of Stochastic Implied Volatility, *Review of Financial Studies*, 6, 293-326

Merton, R. C., (1976), The impact on Option Pricing of Specification Error in Underlying Stock Price Returns, *Journal of Finance*, 31, 333-350

Merton, R. C., (1973), Theory of Rational Option Pricing, *Bell Journal of Economics and Management Science*, 4, 141-183

Patwari, D. C., (2001), *Options and Futures in India Perspective*, 1st edition

Poon, H. S., and C. Granger, (2001), Forecasting Financial Market Volatility A Review, *working Paper*

Rao, S. N., (2003), Black and Scholes-vs-Garch Model: Volatility and Option Pricing, *Working paper*

Tabak, B. M, E. J. Chang, and S. C. Andrade, (2002), Forecasting Exchange rate Volatility, *Working Paper*