Information Content of Option Implied Volatility: Evidence from the Indian Market

S. S. S. Kumar

This paper attempts to investigate the information content of the implied volatility estimators and the historical volatility in forecasting future realized volatility. Implied volatility is computed from the Black-Scholes model and in a regression framework the relationship between different implied volatility estimators and the historical volatility estimator is examined. The results show that implied volatility estimators have information about the future volatility and implied volatility estimators dominate the historical volatility estimator. It is also found that the implied volatility extracted from call options fare better than that computed from put options. Further tests show that implied volatility estimators are unbiased and efficient estimators of the ex post realized volatility. The results also indicate that implied volatility is a rational forecast of future realized volatility.

Keywords: Implied volatility, options, volatility forecasting, historical volatility

Introduction

Volatility forecasting has been an important quest of academic researchers and practitioners for a long time, given the critical role played by volatility in asset pricing and risk management. A plethora of time series and econometric techniques with varying powers of predictability were suggested in the literature to forecast volatility but research in volatility was given a new direction with the publication of a paper by Latane and Rendleman (1976) where they attempt to forecast volatility from traded options. This volatility was called Implied Standard Deviation (ISD) and later on researchers called the same implied volatility (IV).

Typical option pricing models like that of Black and Scholes require as inputs the strike price, stock price, time to maturity, interest rate and expected volatility. Of all the inputs that go into the pricing model only volatility is unobservable yet options trade. This implies that the market participants price the options by arriving at a volatility estimate that impounds all the relevant information reflected in the historical prices and their knowledge about the market conditions that statistical models may fail to capture. Of course this line of reasoning is subject to the assumptions that option markets are efficient, options are priced correctly and the pricing model is correctly specified. Implied volatility is obtained by inverting an option pricing model and this volatility is considered as the market's consensus estimate of future volatility.

S. S. S. Kumar is Associate Professor at Indian Institute of Management Kozhikode, Kozhikode 673570, Kerala, Email: ssskumar@iimk.ac.in

Literature review

Past studies on this theme may be classified into four categories based on their findings: *Implied volatility is correlated with realized volatility*: Initial studies on this theme notably Latane and Rendleman (1976), based on the implied volatility extracted from call options on twenty four companies that are traded on the CBOE found that implied volatility is significantly correlated with actual volatility. Chiras and Manaster (1978) computed implied variances from all the stock options that trade on the CBOE and found that implied variances are better predictors of future variances than historical variance. Latane and Rendleman (1976) had used the European pricing model to extract volatility from American option prices and ignored the dividends but Chiras and Mansater (1978) used the more general Black-Scholes model adjusted for dividends. Beckers (1981) also found that nearest to money, options contain the most information about future volatility.

Implied volatility has no correlation with realized volatility: This far all the researchers agreed that implied volatility contains valuable information about the future volatility and they examined various ways of combining various implied volatility estimators obtained from different strike prices and maturities to obtain a single estimate that had the maximum predictive power. But in the early 90's Canina and Figlewski (1993) using the data from S & P 100 index options drawn from the period March 1983 to March 1987 showed that not only are implied volatility and subsequent realized volatility not correlated, but implied volatility also appears to contain no information at all about realized volatility. The difficulty in constructing arbitrage trades between the underlying index and the options as one reason for their finding.

Implied volatility is correlated with realized volatility and is an unbiased and efficient estimator: Christensen and Prabhala (1998) investigated the relationship between implied and raelized volatility for the S & P 100 index options using the data over Nov 1983 to May 1995. Using non-overlapping data showed that implied volatility does predict future realized volatility and in fact outperforms historical volatility in forecasting future volatility. They argue that the findings of Canina and Figlewski (1993) are due to the pre-crash characteristics and overlap of data relative to time series length. A follow up study by Christensen and Hansen (2002) on the same contract using data over a much longer period proves that implied volatility is not only related to realized volatility but is in fact an efficient forecastor of realized volatility.

Implied volatility is correlated with realized volatility but is a biased estimator: Day and Lewis (1992) using the data on S & P 100 OEX options over the period November 1986 to March 1991 find that implied volatility is related to realized volatility but is a biased estimator. Lamoureux and Lastrapes (1993) demonstrate that implied volatility is a biased estimator of realized volatility. Fleming (1998) presents evidence that implied volatility from the S & P 100 index call and put options is biased but the bias does not throw opportunities to earn economically significant profits. Recently, Szakmary *et al* (2003) using data from eight different exchanges and 32 different contracts demonstrate that implied volatility performs better than historical volatility as predictor of future volatility. From the literature review it may be noted that there is no unanimity on the information content of the implied volatility and its predictive capacity to forecast future volatility. Almost all the studies examined this issue in the developed markets predominantly in the U.S. and there is no study conducted in any of the Asian markets or in the emerging markets even though there are significant trading volumes (as can be seen from Table 1) on the Asian derivative bourses. This paper is an attempt to address this gap by providing evidence from the index options that trade on the National Stock Exchange of India (NSE).

Table 1

Traded volumes of Stock Index Options during 2005-06

Exchange	Number of contracts traded (Volume)
Korea Exchange	2,414,422,955
Chicago Board Options Exchange	279,005,803
Eurex	217,232,549
TAIFEX	99,507,934
Tel Aviv SE	75,539,100
Euronext.liffe	50,279,874
Osaka SE	28,231,169
Chicago Mercantile Exchange	27,295,611
National Stock Exchange India	18,702,248

Source: *WFE Annual Report* 2006, page 102

Overview of Indian options market

Equity derivatives trading commenced on the NSE from June 2000 with the introduction of stock index futures followed by option contracts on index from June 2001. By November 2001, options and futures on individual securities also commenced trading. The underlying asset for the index options and stock index futures which is the S & P CNX Nifty index (Nifty) is a portfolio of fifty stocks and is calculated using the market capitalized weighted method. The index option contracts have a maximum duration of three months; accordingly three contracts are available for trading at any point of time namely near month, next month and far month. The near month contract expires on the last Thursday of the month and from the following day a new contract (for the far month) will be available for trading. On the first day of the introduction the exchange introduces at least nine in-the-money contracts, one at-the-money and another nine out-of-money contracts. Index options that trade on NSE have European style exercise feature and both calls and puts are available for trading. As of March 2007, the notional trading value of index options amounted to Rs.1,133,220 million with the near month contract recording the highest notional trading value of Rs.493,587 million for call options and Rs.476,752 million for put options. As in many other option markets, on NSE also the most liquid contract is the near month contract and volumes in the next month contract will pick up as the near month contract is nearing its expiry date.

Data

In this study we compute the implied volatility of the Nifty index options that trade on NSE. The first observation is that of January 2002 contract and the last observation pertains to the July 2006 contract. We have deliberately not considered the first six months' data since trading is rather thin initially. Our study uses non-overlapping near month option contracts with a time to maturity of 30 calendar days. For example the first observation is for the January 2002 contract expiring on 31-1-2002 so we move back 30 days from the expiry day i.e., on 1-1-2002 observe the inputs to the option pricing model and extract the implied volatility. Similarly the next data point is the implied volatility from the February 2002 contract expiring on 28-2-2002 so the prices on 29-1-2002 will be observed and they will be used to extract implied volatility. In this way the implied volatility series is constructed.

Methodology and research hypotheses

In this work we computed implied volatility from the basic Black-Scholes model. Inverting an option pricing model like that of Black-Scholes is a difficult task therefore generally implied volatility is extracted from the option prices by using some numerical methods viz., Newton-Raphson method; here we computed it (in Microsoft Excel) by equating the difference between observed price of the option and the theoretical price of the option to zero and solving for volatility. The theoretical option prices as per Black-Scholes model are given as:

$$C = S.\, N(d_1) - X.e^{-rt}.N(d_2) \quad (5.1)$$

$$P = X.\, e^{-rt}.\, N(-d_2) - S.\, N(-d_1) \quad (5.2)$$

$$d_1 = \frac{\ln(S/X) + \left(r + \sigma^2/2\right)\cdot t}{\sigma \cdot \sqrt{t}} \quad (5.3)$$

$$\text{and } d_2 = d1 - \sigma\cdot\sqrt{t} \quad (5.4)$$

Where C and P are the call and put option prices, 'r' is the risk free interest rate, 'X' is the strike price, 'S' is the spot price of the underlying, 't' is the time to maturity of the option, 'σ' is the volatility of the underlying over the life of the option and N is the cumulative normal distribution function. The above model is used to price a European style option on a non-dividend paying stock. Since the call and put index options trading on NSE are European in exercise style this model can very well be used in this study. However an important input that is needed for the model is the expected future dividends from the stocks that underlie the Nifty index. One way to incorporate the dividends is to use the actual dividends paid by the stocks but what is required is the ex ante expected dividends and not the ex post dividends. Since the implied volatility is computed from index options rather individual stock options it is not inappropriate if dividends are assumed to be paid continuously. Accordingly the basic Black-Scholes model needs a minor adjustment[1] – substituting 'S' with $S \cdot e^{-d.t}$ where'd' is the continuous dividend rate, and use the adjusted Black-Scholes model considering that the dividends are zero. Therefore in order to compute implied volatility effectively what is needed is precise determination of $S \cdot e^{-d.t}$. Poteshman (2000) suggests using the futures market and the spot-futures parity to obtain it. Spot-futures parity may be stated as

$$F = S \cdot e^{(r-d).t} \quad (5.5)$$

where 'F' is the futures price, 'S' is the underlying's spot price, 't' is the time to maturity, 'r' is interest rate and 'd' is the continuous dividend yield. A slight rearrangement of the terms in the spot-futures parity gives the following expression

$$S \cdot e^{-d.t} = F \cdot e^{-r.t} \quad (5.6)$$

Since there is an active and liquid index futures market on Nifty index we can obtain the term from the futures prices. Accordingly we collected the closing futures prices using the one month Mumbai Inter Bank Offer Rate (MIBOR) as the interest rate and setting't' as time to maturity of the option we arrived at $S \cdot e^{-d.t}$.

Another important question that arises in the estimation of implied volatility is which traded options should be used to estimate implied volatility? At any point of time for the same expiry date there will be many options with different strike prices and each of them can give a different implied volatility estimate. In this study we considered two different types of implied volatility estimators. The first type of implied volatility is computed from those options that have the highest traded volumes and the second type of estimator is from close to at-the-money options referred to as near-to-money (NTM) option i.e., that option for which the difference between the exercise price and the adjusted spot index ($X \sim S \cdot e^{-d.t}$) is minimal. Since implied volatility is considered as the market's consensus estimate of volatility, options that record higher volumes will contain the market's expectations because these are the options on which real money is being put. It may also be noted that quite often options with the highest volumes are also closer to being at-the-money. In that sense these two series are rather highly correlated and Black-Scholes model is not mis-specified for pricing at-the-money options. These volatilities are estimated for both calls as well as put options. Therefore we have two implied volatility series from call options, another two series from put options, a realized volatility series and finally the historical volatility series summing up to six data series. For ease of comprehension we present in Table 2 the different volatility estimators along with the symbols that denote them:

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[1]Any standard textbook on derivatives explains this adjustment. See for instance, Hull (2006), pp 290.

Table 2

Volatility estimators used in the study

Name of the volatility estimator	Denoted as
Realized volatility	σ_R
Historical volatility	σ_H
Implied volatility from call options based on highest volume	σ_{cvol}
Implied volatility from call options based on moneyness	σ_{cm}
Implied volatility from put options based on highest volume	σ_{pvol}
Implied volatility from put options based on moneyness	σ_{pm}

To ensure that the option prices obeyed the inequality restrictions implied by the no-arbitrage conditions on options prices: $C \geq S \cdot e^{-d.t} - X$ and $P \geq X - S \cdot e^{-d.t}$ we checked the option prices data for the same and those observations that violated these relations were not considered. The realized volatility is computed as the annualized standard deviation of the continuously compounded returns from the observed date till maturity of the option i.e., 30 days:

$$\sigma_R = \sqrt{\left(\frac{252}{T_M - 1}\sum_{k=1}^{T_m}\left(R_t - \overline{R}\right)^2\right)} \qquad (5.7)$$

where $R_t = Ln(I_t/I_{t-1})$; I_t is the index level on day 't' and k runs from the expiry day of the option to 30 days (T_M) preceding the expiry day.

The historical volatility is computed as the annualized standard deviation of the continuous compounded daily returns of the stock index 60 days from the option's expiry date till 30 days from the option's expiry date i.e., in essence we computed historical volatility over the same length of time period as that was of the life of the option.

Consistent with earlier research on this theme our research hypotheses are the following:

H1: Implied volatility does not contain information about the ex post realized volatility

For testing this hypothesis we run the following regression known as the 'rationality test' regression by Canina and Figlewski (1993):

$$\sigma_R = \alpha_1 + \beta_1 \cdot \sigma_I + \varepsilon_1 \qquad (5.8)$$

Where σ_R is the realized volatility, σ_I is the implied volatility from different estimators. If implied volatility contains information about future realized volatility we will observe that β_1 will be statistically different from zero.

H2: Historical volatility does not contain information about the ex post realized volatility

In order to verify this hypothesis we run regression (5.9) given below and if the statistics fail to reject $\beta_2 = 0$ then we may infer that historical volatility is a good predictor of realized volatility

$$\sigma_R = \alpha_2 + \beta_2 \cdot \sigma_H + \varepsilon_2 \tag{5.9}$$

H3: Implied volatility estimators do not fare better than historical volatility estimators

To test this hypothesis we compare the R^2 of both regressions (5.8) and (5.9) and if the R^2 of regression (5.8) is higher than that of (5.9) we may infer that implied volatility is better at forecasting the future volatility vis-à-vis historical volatility.

Kirtzman (1991) argues that just based on a higher R^2 one cannot conclude that implied volatility estimators fare better than historical volatility estimator since the slope coefficient may be significantly greater than or less than one and the intercept may also be greater than or less than zero. Therefore he advocates computing the tracking error or RMSE defined in equation (5.10). We also check the tracking error or root mean square error (RMSE) associated with implied volatility and historical volatilities where RMSE is defined as the square root of the average of the squared differences between realized volatility and implied volatility/ historical volatility:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum\left(\sigma_R - \sigma_j\right)^2} \tag{5.10}$$

Where σ_R = the realized volatility, σ_j = implied or historical volatility as the case may be and n = number of observations.

H4: Implied volatility incorporates information that is not captured by historical volatility

For testing the fourth hypothesis we run the following regression which is referred to as the encompassing regression by Canina and Figlewski (1993)

$$\sigma_R = \alpha_3 + \beta_3 \cdot \sigma_I + \lambda_3 \cdot \sigma_H + \varepsilon_3 \tag{5.11}$$

If implied volatility is based on a larger set of information and historical volatility is based only on a subset of information of the investment community then in the above regression we will observe that $\alpha_3 = 0$ and $\beta_3 = 1$ and $\lambda_3 = 0$.D

Results and Discussion

Table 3 presents the descriptive statistics of all the volatilities estimators along with realized volatility. It may be noted that the average realized volatility is lower than any of the average implied volatility series. But the dispersion of the realized volatility is more than the implied volatility series which is in consonance with the customary acknowledged view that implied volatility is a smoothed expectation of realized volatility. Further it can be observed that realized volatility is more skewed and more fat tailed than any of the implied volatility series and also it appears that implied volatility series are closer to normal distribution than realized volatility. But the Jarque-Bera test for normality rejects the null hypothesis that the data series are normal for all the volatility series though the statistic is smaller for the implied volatility estimator.

Table 3

Descriptive statistics

	σ_R	σ_H	σ_{cvol}	σ_{cm}	σ_{pvol}	σ_{pm}
Mean	0.2010	0.2003	0.2141	0.2104	0.2170	0.2163
Std. Dev.	0.0986	0.0788	0.0585	0.0570	0.0682	0.0715
Skewness	2.5845	2.0018	1.2368	1.0324	1.0351	1.3827
Kurtosis	10.9478	6.5125	4.5174	3.5254	4.4266	5.8844
Jarque-Bera	205.9903	65.0044	19.2981	10.4038	14.4854	36.5909
Probability	0.0000	0.0000	0.0001	0.0055	0.0007	0.0000

We first tested for autocorrelation in the realized volatility series as the presence of autocorrelation is an indication of the predictability of volatility. The first order auto correlation at 0.424 is significant as the corresponding Q-statistic is 10.448 ($p = 0.001$). Presence of autocorrelation may be considered as an evidence of persistence i.e., a low volatile period will be followed by low volatile periods and vice-versa.

Table 4

Autocorrelation and Partial auto correlations of realized volatility

Lags (k)	AC	PAC	Q-Stat	P-Value
1	0.424	0.424	10.448	0.001
2	0.219	0.047	13.274	0.001
3	0.074	-0.041	13.608	0.003
4	0.071	0.055	13.922	0.008

AC denotes the autocorrelation coefficient for the data that are k periods apart and PAC is the partial autocorrelation coefficient after removing the correlation from the intervening lags. Q statistics are the Box-Ljung Q statistics at respective lags test the null hypothesis that there is no autocorrelation up to order k.

Next we test for the unit roots in the data series as presence of unit roots is evidence that the time series is not stationary least square estimates are not consistent and inferences from conventional regressions do not hold as the relationships may be spurious. Normally unit roots are tested using the Augmented Dickey-Fuller tests but a major criticism on these tests is that they cannot differentiate between unit root and near unit root process i.e., the power of the tests is low when the process is stationary but the root is close to the non-stationary boundary. For instance Szakmary et al (2003) used ADF tests and found that they can not reject unit root in one of the data series and conclude by noting that "failure to reject the unit root null hypothesis for implied volatility series of sugar futures is likely due to the low power of the ADF test rather genuine non-stationarity". Hence in our study we use Kwiatskowski-Phillips-Schmidt-Shin (KPSS) Kwiatkowski et al (1992) method for testing stationarity. KPSS tests the null hypothesis that a time series is stationary versus an alternative hypothesis that the series is a unit root process. In this procedure the time series is considered to be a sum of deterministic trend, a random walk, and a stationary error term in the following way:

$$y_t = r_t + \lambda t + \varepsilon_t \tag{6.1}$$

where r_t is a random walk, i.e., $r_t = r_{t-1} + u_t$, and u_t is i.i.d $(0, \sigma_u^2)$; λt is a deterministic trend; ε_t is a stationary error. In the KPSS tests the null hypothesis could be either trend stationarity or level stationarity. If the series is stationary around a deterministic trend, the null hypothesis will be $\sigma_u^2 = 0$, against the alternative of $\sigma_u^2 > 0$. To test the null hypothesis of level stationarity, i.e., the time series is stationary around a fixed level, λ will be set equal to zero. The KPSS test statistic is given as:

$$\text{KPSS test statistic } \eta = T^{-2} \frac{\sum_{t=1}^{T} S_t^2}{s^2(l)} \tag{6.2}$$

Where S_t is the partial sum of deviations of residuals from the sample mean, and $s^2(l)$ is a consistent estimate of σ_u^2 given as under:

$$s^2(l) = T^{-1} \sum \hat{\varepsilon}_t^2 + 2T^{-1} \sum_{j=1}^{l} \theta(j, L) \sum_{j=1}^{t} \hat{\varepsilon}_t \hat{\varepsilon}_{t-j} \tag{6.3}$$

T is the sample size, l is the lag truncation parameter and $\theta(j, l)$ is an optional weighting function that corresponds to the choice of a spectral window, and KPSS use the Bartlett window $\theta(j, l) = (1-j/l+1)$ as in Newey and West (1987). For large values of the test statistic H_0 is rejected in favor of H_1.

Table 5

KPSS Stationarity tests

Volatility	η_1	η_2
σ_R	0.1843	0.0825
σ_H	0.1102	0.1007
σ_{cvol}	0.2637	0.0757
σ_{cm}	0.2518	0.0819
σ_{pvol}	0.3331	0.0752
σ_{pm}	0.3473	0.0782

KPSS test statistics η_1 and η_2 tests the null of level and trend stationarity respectively. The test employs a Newey – West type variance estimator of the long run variance of ε_t. The 5% critical value is 0.463 when the null hypothesis is stationarity and for the null of trend stationarity the critical value is 0.146

From the KPSS test we can conclude that all of the volatility series are stationary and we can test our hypotheses in the regression framework. Table (6) presents the results of regression (5.8)

Table 6

Realized volatility regressed on different implied volatility estimators:

Equation: $\sigma_R = \alpha_1 + \beta_1 \cdot \sigma_I + \varepsilon_1$

Independent variable		α_1	β_1	Adj R^2
σ_{cvol}	Coefficient	0.0152	0.8679	0.2511
	t-statistic	0.3458	4.3709	
	p-value	(0.7309)	(0.0001)	
σ_{cm}	Coefficient	0.0203	0.8591	0.2351
	t-statistic	0.4518	4.1665	
	p-value	(0.6532)	(0.0001)	
σ_{pvol}	Coefficient	0.0467	0.7111	0.2278
	t-statistic	1.1899	4.1151	
	p-value	(0.2394)	(0.0001)	
σ_{pm}	Coefficient	0.0599	0.6521	0.2091
	t-statistic	1.5793	3.9087	
	p-value	(0.1202)	(0.0003)	

Least squares estimates of the regression $\sigma_R = \alpha_1 + \beta_1 \cdot \sigma_I + \varepsilon_1$. The implied volatility is computed using the Black-Scholes option pricing model from both call and put options with highest traded volumes and those that are near-to-the-money defined as the option's strike price closer to $S \cdot e^{-dt}$. The realized volatility is computed as the annualized standard deviation of the continuously compounded returns from the option's expiry date to the preceding 30 days. For all four types of estimators the same regression is estimated. The data consist of 55 monthly non-overlapping observations of each volatility series over the period Jan 2002 to July 2006.

Since the slope coefficients are significant irrespective of the implied volatility estimator it may be inferred from the regression results that implied volatility is a good predictor of realized volatility whether it is estimated from call options or put options although R^2 of the regressions from call options is highest. Therefore we can reject the null hypothesis that implied volatility does not contain information about the realized volatility and the results show that implied volatility estimators are reasonably correlated with the future realized volatility. Table (7) below presents the regression results that test whether historical volatility contains information about the future realized volatility.

Table 7

Realized volatility regressed on historical volatility:

Equation $\sigma_R = \alpha_2 + \beta_2 \cdot \sigma_H + \varepsilon_2$

Independent variable		α_2	β_2	Adj R^2
σ_H	Coefficient	0.1211	0.3990	0.0847
	t-statistic	3.459	2.449	
	p-value	0.0005	0.01439	

Least squares estimates of the regression $\sigma_R = \alpha_2 + \beta_2 \cdot \sigma_H + \varepsilon_2$. The historical volatility is computed as the annualized standard deviation of the continuous compounded daily returns of the stock index 60 days from the option's expiry date till 30 days from the option's expiry date. The realized volatility is computed as the annualized standard deviation of the continuously compounded returns from the option's expiry date to the preceding 30 days. The data consist of 55 monthly non-overlapping observations of historical and realized volatility series over the period Jan 2002 to July 2006.

It may be inferred that the historical volatility[2] contains information about the future realized volatility. From the Adj. R^2 figures it may be inferred that implied volatility has more explanatory power historical estimator. The computed RMSEs are shown in Table 8 and it can be noted

[2] The regressions were estimated for alternate estimators of historical volatility viz., it is estimated using past 60 days data but the results remain qualitatively the same. These results will be available on request.

that even on the basis of RMSE implied volatility estimators dominate the historical volatility estimator that has the highest tracking error. Here again the implied volatility from call options has less tracking error vis-à-vis the implied volatility from put options.

Table 8

RMSEs (in %) of the different volatility estimators

Volatility estimator	RMSE
σ_{cvol}	8.51%
σ_{cm}	8.56%
σ_{pvol}	8.87%
σ_{pm}	9.08%
σ_H	13.27%

RMSE is defined as the square root of the average of the squared differences between realized volatility and implied volatility or historical volatility as the case may be.

Now there is reasonable evidence that implied volatility estimators fare better than historical volatility estimators. We also conducted tests to see whether implied volatility estimators are unbiased and efficient estimators of realized volatility. If an estimator is unbiased then we will observe that the intercept term (α) of the regression will be equal to zero and the slope coefficient (β) will equal 1. Poon and Granger (2003) observe that an estimator is upwardly if $\alpha > 0$ and $\beta = 1$ or $\alpha = 0$ and $\beta > 1$. But if $\alpha > 0$ and $\beta < 1$ then the implied volatility under estimate, low volatility and over estimates high volatility. We conducted a Wald Test to test the joint hypothesis $\alpha_1 = 0$ and $\beta_1 = 1$ of the regression (5.8) and the results are presented below:

Table 9

Wald Test Statistics

Volatility estimator	F –statistic	p-value
σ_{cvol}	0.8638	0.4274
σ_{cm}	0.5558	0.5768
σ_{pvol}	2.3285	0.1073
σ_{pm}	3.0119	0.0577
σ_H	6.8042	0.0023

The null hypothesis is Ho: $\alpha_1 = 0$ and $\beta_1 = 1$ where the coefficients are obtained from the regression equation (7). Rejection of the null hypothesis means implied volatility is a biased estimator of realized volatility.

From the Wald test it may be inferred that the joint hypothesis of $\alpha_1 = 0$ and $\beta_1 = 1$ cannot be rejected for the implied volatility estimators though the implied volatility estimator derived from the NTM put options seems to be biased at the 10% level of significance. The null hypothesis is rejected at all conventional levels of significance for the historical volatility estimator which means that it is a biased estimator.

If the implied volatility estimator is an efficient estimator then the residuals from the regression should be Gaussian white noise. This is examined by conducting the ARCH LM test on the regression residuals and the results are presented in Table 10. It may be noted that in none of the cases the null hypothesis that the residuals are a Gaussian white noise process is rejected, hence it may be concluded that the implied volatility estimator contains information about the future realized volatility and it is an unbiased and efficient estimator.

Table 10

ARCH LM Test Statistics

Volatility estimator	Test statistic	p-value	Inference at 5%
σ_{cvol}	0.2979	0.5851	Accept Ho
σ_{cm}	0.3646	0.5459	Accept Ho
σ_{pvol}	0.0324	0.8571	Accept Ho
σ_{pm}	0.0105	0.9183	Accept Ho

Null hypothesis: ε_t is Gausssian white noise and the Alternative hypothesis: $V(t) = a(0) + a(1)u^2_{(t-1)} + .. + a(p)u^2_{(t-p)}$, where V(t) is the conditional variance of ε_t. The ARCH test is the LM test of the joint hypothesis $a(1) = .. = a(p) = 0$

Further following Figlewski (2004) we examined the residuals from the regression for their correlation with the independent variable and we find that there is no correlation between the error term and the forecast so we can conclude that implied volatility is a rational forecast of the realized volatility.

Now we will present the results that test our fourth hypothesis whether implied volatility impounds information that is not contained in historical volatility.

Table 11

Realized volatility regressed on implied volatility and historical volatility:

Equation $\sigma_R = \alpha_3 + \beta_3 \cdot \sigma_I + \lambda_3 \cdot \sigma_H + \varepsilon_3$

Independent variable		α_3	β_3	λ_3	Adj R^2	F-statistic	p-value
σ_{cvol}	Coefficient	0.007881	1.163502	-0.27923	0.2565	10.3142	0.0001
	t-statistic	0.177809	3.639119	-1.1768			
	p-value	0.8596	0.0006	0.2446			
σ_{cm}	Coefficient	0.014681	1.090684	-0.21525	0.2299	9.0586	0.0004
	t-statistic	0.32322	3.314714	-0.90412			
	p-value	0.7478	0.0017	0.3701			
σ_{pvol}	Coefficient	0.048048	0.748751	-0.04729	0.2134	8.3412	0.0007
	t-statistic	1.199674	3.114223	-0.22716			
	p-value	0.2357	0.003	0.8212			
σ_{pm}	Coefficient	0.059777	0.648434	0.004932	0.1939	7.4953	0.0014
	t-statistic	1.523161	2.859831	0.023961			
	p-value	0.1338	0.0061	0.9810			

In ordinary least squares estimates of the regression $\sigma_R = \alpha_3 + \beta_3 \cdot \sigma_I + \lambda_3 \cdot \sigma_H + \varepsilon_3$, different implied volatility estimators one at a time along with historical volatility are used as determinants of the realized volatility. The F-statistic tests the joint hypothesis that $\beta_3 = \lambda_3 = 0$.

From these encompassing regression results it may be noted that only the slope coefficient of implied volatility is statistically significant and the intercept term and the coefficient of historical volatility estimator terms are not statistically significant i.e., statistically speaking $\alpha = 0$, $\beta \neq 0$ and $\gamma = 0$. Therefore it may be inferred that implied volatility estimators contain all the information that is included in historical volatility estimators and including historical volatility estimators do not lead to any improvement in R^2 except for one case where the independent variable is the implied volatility obtained from call options that have highest traded volumes, but still the improvement may not be economically significant enough.

The results of our study support the proposition that implied volatility is an unbiased and efficient predictor of future realized volatility and our results are in concurrence with past studies of Christensen and Prabhala (1998), Poteshman (2000), Christensen and Hansen (2002) and Szakmary et al (2003). The slope coefficients obtained for the Indian market compare with those of Beckers (1981) and Day and Lewis (1993). However the R^2 of our study falls quite short of the R^2 reported by Beckers (1981) or Day and Lewis (1993)

Conclusions

In this paper we investigated an important question on volatility forecasting that was thoroughly researched in the options markets of the developed countries but not studied in any of the Asian markets or emerging markets. The main research question investigated in this study pertains to the information content of the implied volatility estimators and from the results we can conclude the following:

1. The mean implied volatility computed from either call or put options is lower than the realized volatility whereas the dispersion of realized volatility is more than that of the implied volatility estimators.

2. We reject the hypothesis that there is no relationship between implied volatility and realized volatility and implied volatility estimated from call options that have the highest trading volumes has the highest explanatory power and R^2 of the regression is comparable to that reported by Christenson and Prabhala (1998)

3. Historical volatility also contains information about realized volatility but the explanatory power of historical volatility is lower than that of the implied volatility estimator.

4. We also find that implied volatility is an unbiased and efficient predictor of realized volatility whereas historical volatility is a biased estimator.

5. Finally we find that implied volatility embodies more information than that contained in the historical prices.

6. The implied volatility is proved to be a rational forecast of the realized volatility. It may be noted that the adj R^2 is only around 25% which may indicate that there is sufficient unexplained variation but the R^2 obtained from using historical volatility as independent variable is much less than that observed for implied volatility estimators.

Our study has one limitation – implied volatility is computed from the closing prices of the index options and futures and not from temporally matched price series which is considered as a way to avoid the non-synchronous prices problem. Time-stamped data may be an apt solution for options on individual stocks but not with index options from which implied volatility is estimated. This is because the underlying index itself is not traded and is based on fifty underlying stocks and even if one stock does not trade at the same time as the traded option, the problem of non-synchronous prices persists even though temporally matched prices are used.

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