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Assessing the Effectiveness of Implied Volatility in Predicting Realised Return Volatility for Informative Decision-Making: Insights from the Nifty Bank Index

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Abstract

Implied volatility (IV) is crucial in option pricing models and serves as an essential tool for volatility traders to make informed decisions. However, its effectiveness in predicting realized return volatility is still debated. This study investigates the efficiency of implied volatility in forecasting realized return volatility in the Indian financial markets, specifically using Bank Nifty index options and also assesses the predictive capability of implied volatility against the realised volatility estimator. Utilizing data spanning five years, from January 2018 to December 2022. Finding of this study reveal that implied volatility significantly forecasts realized volatility, highlighting its efficacy as a forecasting tool. Moreover, historical volatility fails to enhance predictive power when combined with implied volatility. Nonetheless, caution should be exercised in generalizing these results to other markets or time periods, as further research is warranted. The study contributes to the ongoing discourse on implied volatility efficiency, offering practical insights for options traders and adding to the body of knowledge in financial economics.

Keywords: Bank Nifty, Black-Scholes Model, Derivatives, Implied Volatility, Market Efficiency, Options, Option Pricing.

Introduction

Implied volatility (IV) is a critical component in the most popular Option Pricing model developed by Black-Scholes. IV is highly regarded by volatility traders for making inferences and trading decisions. The Black-Scholes model relies on five key variables: exercise price, underlying price, time to maturity, risk-free rate of interest, and volatility, to determine the option's premium value (1). Among these, volatility is unique as it is not directly observable and is instead derived from the market pricing of the option. IV is calculated by reversing the Black-Scholes model, solving for variance based on the market price of the option. Implied volatility acts as a proxy for the market's forecast of the future return volatility of the underlying asset over the option's remaining life (2). There is a common assumption that the market assimilates all accessible public information to shape expectations regarding future volatility. This perception underscores IV as a reliable gauge of the market's genuine estimation of volatility (3). This assumption has spurred numerous studies with mixed results on the informational efficiency of IV. This study aims to analyse the efficiency of IV in predicting realized return volatility in the Indian market, particularly through Bank Nifty index options. Beyond its role in option pricing models, IV is a vital tool for volatility traders, guiding their strategies and decisions. Through the analysis of IV, traders obtain insights into how the market anticipates future volatility, enabling them to adjust their positions accordingly. Despite its widespread use, the effectiveness of IV as a predictor of realized return volatility remains debated. This research adds to the ongoing discussion by investigating the efficiency of IV in predicting realized return volatility within the Indian market context, with a specific focus on Bank Nifty index options. Numerous strategies such as Short Straddles and Iron Condors are built around volatility and its properties. Traders depend upon the volatility estimators to deploy these strategies.

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Thus, it is of utmost importance for the estimator to be accurate and efficient in its information content. The findings provide practical insights for options traders, enhancing their understanding of IV as a forecasting tool and adds further knowledge on the reliability of other volatility estimators such as historical volatility, enabling traders to make more accurate trading decisions in volatile markets.Through analysing prior studies, firstly it is noted that using historical data to estimate variance led to overpricing of options on high-variance stocks and under-pricing of options on low-variance stocks (4). Pioneers in assessing the effectiveness of implied volatility, explored if implied volatility in stock call options predicts future volatility better than traditional historical measures using cross sectional averages of weighted implied standard deviation. They concluded that the implied estimator outperformed the historic estimator (5). This was further corroborated by a study that examined options from the CBOE and NYSE using implied standard deviation, affirming that at-the-money options largely incorporate pertinent information into their pricing (1). In an investigation, of the pricing efficiency of call options on the NYSE Composite Index and S&P500 through a GLS version of the nonlinear regression procedure of study (6, 7), it was concluded that implied volatility closely reflects actual realized volatility. A study in currency derivatives using moving averages and the GARCH model showed that, implied volatility serves as an efficient but biased predictor of future return volatility for foreign currency futures (8). The relationship between implied and realized volatility in Danish at-the-money call and put options based on the KFK share index from 1995 to 1999 was examined using OLS and 2SLS models. The findings indicated that implied volatility embedded in call and put options efficiently predicts realized return volatility, demonstrating less bias compared to historical volatility (9). Further, the information content of implied volatility in S&P 100 index options over 139 months, using monthly non-overlapping datasets and concluded that implied volatility predicts future realized volatility effectively both independently and in conjunction with past realized volatility (10). Researchers studied the predictive accuracy of Chicago Board Options Exchange (CBOE) implied volatility indices based on Nasdaq 100 and Standard and Poor's 100 and 500 stock indices by employing OLS regression and GARCH models. Their analysis revealed that models incorporating implied volatility as an explanatory variable achieved the highest regression R-squared values, underscoring the efficiency of implied volatility over historical volatility (11). The informational content of implied volatility in sweet crude oil futures traded at the New York Mercantile Exchange and affirmed that implied volatility effectively predicts future realized volatility, with historical volatility adding minimal additional information (12). Further on, the information content of implied and historical volatility in NIFTY 50 Options from 2002 to 2006 was examined through OLS regression, concluding that implied volatility serves as an unbiased and efficient predictor of realized volatility, outperforming historical volatility (13). The efficiency of implied volatility of options on the S&P CNX Nifty index over a decade, concluded that average implied volatilities better explain future realized volatility compared to historical volatility, which was concluded as a biased estimator (14)

In contrast, some researchers concluded that implied volatility lacks efficiency in predicting future realized volatility (15-17). A study examined the implied volatility from equity options and found it insufficient for forecasting future volatility (15). Researchers studied the implied volatility from S&P 100 index call options, noting no statistically significant correlation between implied volatilities across various maturities and moneyness and realized volatility (16). Further, another study that employed GARCH models and monte-carlo simulations to analyse volatility, revealed that implied volatility tends to underestimate realized variance (18). A study by Becker, on the informational efficiency of the S&P 500 implied volatility index (VIX) using GARCH, Stochastic modelling, concluded that it does not reliably predict future volatility (19). Researchers examined the implied volatility's relationship with realized volatility using S&P/ASX 200 index options from April 2001 to March 2006 using OLS and multivariate regressions, and found no significant relationship for implied call volatility (20). A study explored the Indian market's implied volatility's efficiency in predicting realized future volatility using one-month call options on CNX Nifty from June 2001 to December 2014, and concluded that implied volatility did not explain volatility as effectively as historical volatility and tended to overestimate future volatility (21). This research addresses the gap in existing studies by focusing on implied volatility in the Indian options market. Very few studies have explored the efficiency of implied volatility specifically in Bank Nifty index options. The derivatives trading on Bank Nifty exhibits huge levels of volume based on the number of futures and options contracts traded. Bank Nifty is one of the oldest, most reliable, and highly liquid index for derivatives trading compared to other indices like fin nifty which were launched recently in the past few years. Further, events such as the discontinuation of derivatives trading on the Nifty IT index in 2020, made the popularity and dependency on Bank nifty further higher for day traders. Directional traders, day traders, and scalpers often depend upon volatility to make trading decisions and Bank Nifty, owing to its high correlation between the stocks, provides that required level of volatility, making it ideal for trading. Table 1 illustrates the average volatility in various Indian indices.

Table 1: Various Indices and their Volatility (22)

Index	5-Years Standard Deviation	Standard Deviation Since Inception
Nifty 50	18.95	22.89
Midcap Nifty	22.41	25.77
Nifty Next 50	19.44	25.74
Bank Nifty	25.75	28.70

A higher standard deviation indicates greater volatility. Bank Nifty shows the highest volatility both recently and historically. Midcap Nifty has the highest five-year standard deviation, while Nifty 50 has the lowest since inception. Despite exhibiting the highest volatility among the other indices, the lack on research on volatility measures on the Bank Nifty index, forms the very basis of our study. Previous global and Indian studies have yielded conflicting conclusions regarding the efficiency of implied volatility. While few studies support the efficiency of implied volatility in predicting future return volatility (13, 14), others question its efficacy compared to historical volatility. To fill this gap, this study uses implied volatility as an explanatory variable to predict realized volatility in the Bank Nifty index.

Research Hypotheses

The study would explore the following hypotheses around the context of the informational efficiency of implied volatility (13, 21).

H_1: Implied Volatility effectively predicts future realized volatility.

$$\sigma(RV) = \alpha 1 + \beta 1\ \sigma(IV) + \varepsilon \quad \text{[1]}$$

Where σ(RV) is the realised return volatility and σ(IV) is the implied volatility. The above equation will be tested through a simple Ordinary Least-Squared Regression. If implied volatility provides insights into estimating future volatility, then β must be different than zero and should be significantly higher for it to be an efficient predictor.

H_2: Historical volatility effectively predicts future realized volatility.

$$\sigma(RV) = \alpha 2 + \beta 2\ \sigma(HV) + \varepsilon \quad \text{[2]}$$

Thus, if historical volatility is not efficient in forecasting the future realised volatility it will be observed that β2=0 or close to 0 for that case and the null will be accepted.

H_3: Implied volatility encapsulates information beyond what historical volatility captures.

$$\sigma(RV) = \alpha 3 + \beta 3\ \sigma(IV) + \lambda\ \sigma(HV) + \varepsilon \quad \text{[3]}$$

If the above hypothesis is true, and if, α3=0, β3=1 and λ=0, It can be inferred that implied volatility estimators encompass all the information contained in historical volatility estimators, and incorporating historical volatility does not enhance the overall predictive efficiency of the model.

Methodology

The time-period for the data in consideration will be 5 years, Ranging from 25-01-2018 to 29-12-2022. The data for closing price of the Bank Nifty index, option prices and dividends paid out on the underlying asset, are directly downloaded from the NSE website and Bloomberg (22). The India 10-Year Government Bond Yield serves as the proxy for the risk-free rate. The implied volatility data was collected from continuous Bank Nifty index call and put options with one month to maturity. The monthly expiries are used for the study since weekly expiries provide a very narrow time-period for the market to price them, leading to inefficient pricing of the options and are further affected by speculators who often trade in weekly expiries. These monthly options expire on every- last thursday of the month. Hence for every corresponding month't', the options data regarding the strike-price and premium of the at-the money option was recorded on the day next to the monthly expiry day of the previous month,'t-1'. Subsequently, the historical volatility is calculated using the index return values between the day next to the monthly expiry day of the previous month, 'p1' and the expiry day of the current month 'p2'. Figure 1 illustrates how historical volatility and realised volatility data was collected for each monthly period:

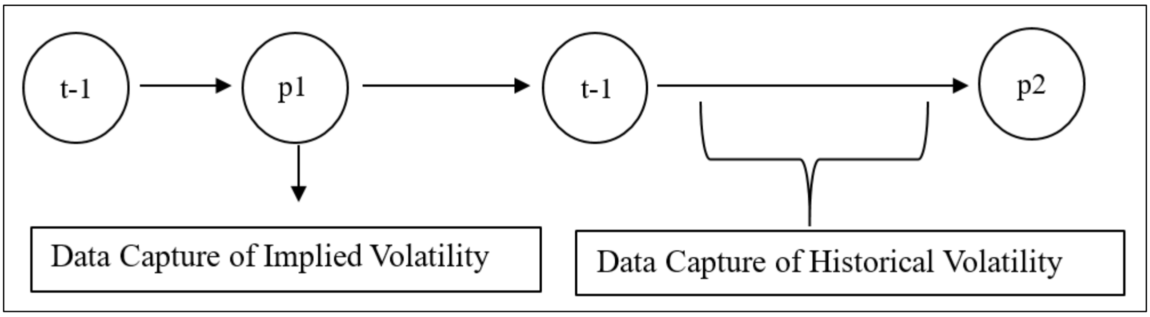

Figure 1: Framework of Data Collection for Volatility

Given that call and put options exhibit nearly identical implied volatilities and liquidity levels, the study considers the average implied volatility of both types of options (23).

AVG_IV= 1/2 (Call IV) + 1/2 (Put IV)……………… [4]

At-the-money options with one month till expiry will be considered for the study; since options that are out of the money might contain less information about the implied volatility and have less liquidity, making them inefficient in their pricing. This is further supported by the research who found that implied volatility from at-the-money options are better predictors of future realised volatility compared to implied volatility of in- or out-of-the-money options (16, 23). The implied volatility for each option under study will be determined manually by solving the Black-Scholes Option pricing model in reverse:

$\sigma(IV)= BS^{1}(S_{0,} t, K, r, \sigma)$ ………………………………[5]

Where,

$BS^{-1} (S_{0,} t, K, r, \sigma) = S_0N(d_1)\text{-}Ke^{-rT} N(d_2)$

Hence implied volatility is calculated as a function of the current price of the underlying asset (S_0), time to expiration (t), strike price (K), risk-free interest rate (r), and the standard deviation of the underlying asset's returns (σ). The Realised Volatility of the index will be calculated by using the following formula using the adjusted closing Prices of the Bank nifty index:

$$\sigma(RV) = \sqrt{\frac{\Sigma \quad (r_t - r_m)^2}{N-1}} \times \sqrt{252} \text{………………… [7]}$$

Where r_t= ln (I_t/I_{t-1}); I_t is the index level on day't' and r_m is the mean of the series. The realised volatility is then annualised so that it is consistent with the implied volatility estimate. In this manner, each monthly period includes an ex-ante forecast of implied volatility and an ex-post calculation of realized volatility. Therefore, there will be 12 data points in one year and 60 data points in 5 years. In addition, the lagged realised volatility is taken as Historical Volatility estimator with a lag of 1.

$HV_t = RV_{t-1}$ ………………………………. [8]

Thus, this constitutes our third data series. Subsequently, the data series of Realised volatility (Series 1) will be regressed with the data series of Implied Volatility (Series 2) and Historical Volatility (Series 3), using an Ordinary Least Squared Regression. Hence, the Efficiency of Implied Volatility in predicting the Future Volatility can be tested along with the efficiency of historical volatility. Table 2 shows the description of each variable, unit of measurement, frequency and its sources.

Table 2: Description of the Variables

Variable	Unit of Measurement	Frequency	Source
Average Implied Volatility (AVG_IV)	Standard Deviation	Monthly	Bloomberg
Historical Volatility (HV)	Standard Deviation	Monthly	Bloomberg
Realized Volatility (HV)	Standard Deviation	Monthly	Bloomberg

Results and Discussion

The study employed descriptive statistics, unit root test and ordinary least square method to accomplish the objective of the study.

Descriptive Statistics

The following Table 3 presents the descriptive statistics for all the volatility series.

Table 3: Descriptive Statistics

	AVG_IV	HV	RV
Mean	24.12392	22.09874	22.11785
Std. Dev	11.66045	14.65297	14.63867
Skewness	2.255955	3.110980	3.118328
Kurtosis	9.754295	15.24327	15.28432
Jarque-Bera	164.9446	471.5259	474.5007
Probability	0.000000	0.000000	0.000000

It is noted that, the mean of both realised volatility and historical volatility is lower than that of the average implied volatility. Both realised volatility and historical volatility exhibit analogous patterns, with substantial volatility (SD ≈ 14.65) and positively skewed, highly leptokurtic distributions. The implied volatility demonstrates considerable variability (SD = 11.66) and a positively skewed, leptokurtic distribution The Jarque-Bera tests suggest that all three variables deviate from normal distributions, supported by extremely low associated probabilities (close to 0.000).

Time Series Plot of Implied and Realized Volatilities

Figures 2 and 3 show the graphical representation of time series of the implied and historical volatility series against the realised volatility.

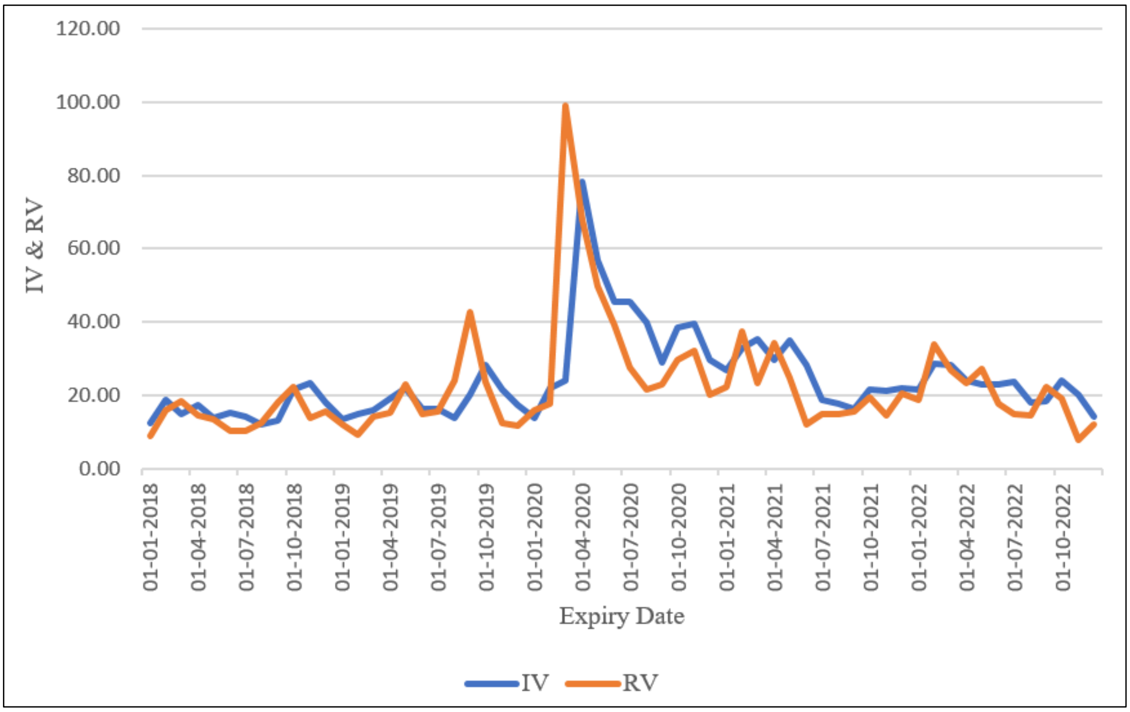

Figure 2: Implied and Realized Volatility

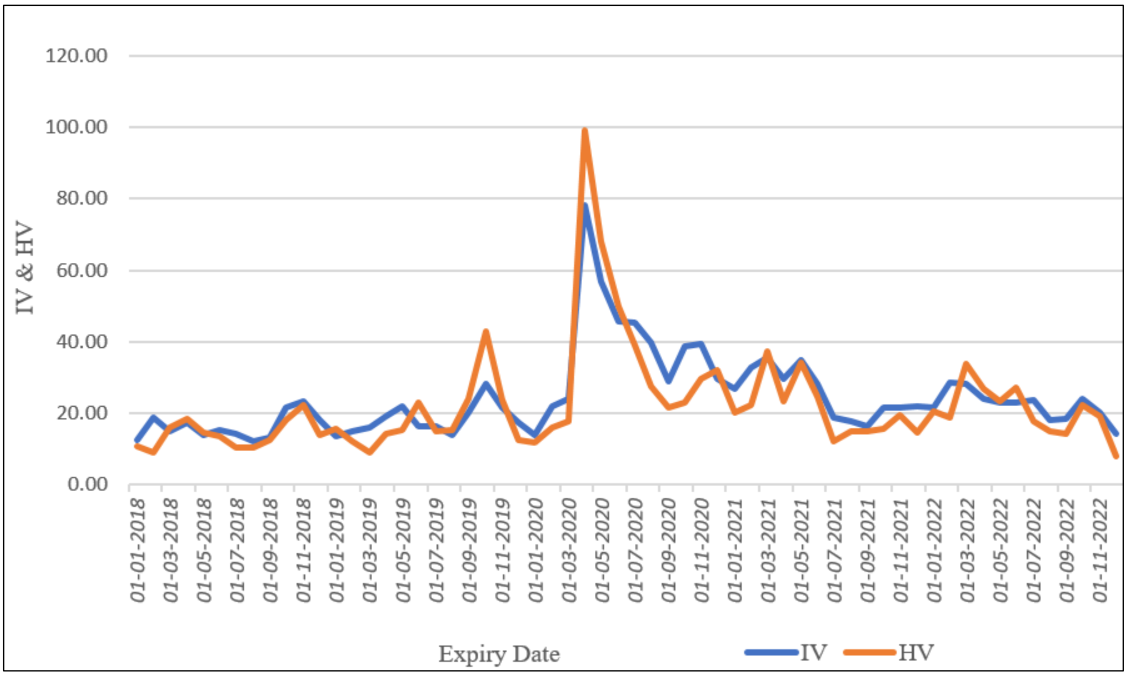

Figure 3: Implied and Historical Volatility

Figure 2 and 3 shows that implied and realized volatilities do not perfectly match, indicating that neither implied volatility nor historical volatility perfectly predicts future realized volatility, highlighting a discernible disparity between the two series. Given that unit roots indicate non-stationarity in data, the study employs the Augmented Dickey-Fuller test to assess their presence which is provided in Table 4.

Table 4: Unit Root Test, at Level (With Trend and Intercept)

Volatility	t-Statistic	Probability
AVG_IV	-3.227	0.0233**
RV	-0.408	0.0021*
HV	-0.402	0.0025*

Note: * and ** indicates significant at 1 and 5 percent significance level

The ADF tests conducted on AVG_IV (Average Implied Volatility), RV (Realized Volatility), and HV (Historical Volatility) reveal insightful findings. AVG_IV demonstrates statistical evidence for stationarity with a t-statistic of -3.227 and a corresponding probability of 0.0233, indicating rejection of the non-stationarity null hypothesis at the 5% significance level. Similarly, both RV and HV exhibit indications of stationarity, supported by t-statistics of -0.408 and -0.402, respectively, coupled with probability values of 0.0021 and 0.0025, below the 5% significance level. Hence the null hypothesis is rejected at the 5% level. These results suggest that all three-volatility metrics exhibit stationary behaviour.

Table 5: Results of Ordinary Least Square Method

Equation: $\sigma(RV)= \alpha1+ \beta1\ \sigma(IV)+\varepsilon$

Independent Variable		Coefficient	Standard Error	t-statistic	Probability Value	F-Stat	R^2	DW
AVG_IV	α	3.87	3.519	1.100	0.275	33.043	0.36	1.82
	β	0.75	0.131	5.748	0.000*			

*Note: * indicates significant one percent level*

Table 5 shows the summary of ordinary least square method. The intercept coefficient, representing the expected realized volatility when average implied volatility is zero, was found to be 3.87, albeit not statistically significant. However, the slope coefficient indicated a significant positive relationship between realized volatility and average implied volatility, with a one-unit increase in average implied volatility corresponding to a 0.75-unit increase in realized volatility. This relationship was statistically significant with a very low p-value, indicating its robustness. The overall regression model was statistically significant, as indicated by the F-statistic, and the R-squared value of 0.36 suggested that 36% of the variation in realized volatility could be explained by average implied volatility. Additionally, the Durbin-Watson statistic of 1.94 suggests that there is minimal positive autocorrelation in the residuals. This means that the errors in the regression model are somewhat correlated with each other, but not to a significant extent. Therefore, the assumption of independence of errors, which is crucial for the validity of OLS regression analysis, seems to be reasonably satisfied. Thus, the null hypothesis that implied volatility is not an efficient predictor of realised volatility is rejected since $\beta1\neq0$. Further, the study residual diagnostics employed to test the estimated model is good or not. The result of autocorrelation and heteroscedasticity test with lag 2 given in the below Table 4 and formulated the hypothesis accordingly.

Heteroscedasticity test –Hypothesis:

H_0 – There is homoscedasticity in the error term

H_1 – There is heteroscedasticity in the error term

Serial Correlation LM- test –Hypothesis:

H_0 – There is no autocorrelation in the error term

H_1 – There is an autocorrelation in the error term.

Table 6: Testing of Residual Diagnostics

Test	p value of Chi-square	Decision
Autocorrelation	0.852	Accept H_0
Heteroscedasticity	0.66	Accept H_0

Table 6 explains the residual diagnostics of estimated OLS mode. As per the output properties of classical linear regression model, the estimated OLS model does not have the presence autocorrelation and heteroscedasticity in the error term since the probability value of chi square is greater than 5 percent. Therefore, the model's estimates and inferences regarding average implied volatility are unlikely to be biased due to serial correlation within the specified lag range. Hence, the H_0 is accepted.

Table 7: Estimation of Historical Volatility on Realized Volatility

Equation: $\sigma(RV)= \alpha2 + \beta2\ \sigma(HV)+ \varepsilon$

Independent		Coefficient	Standard Error	t-statistic	Probability Value	F-Stat	R^2	DW
Intercept	α	9.80	2.880124	3.405804	0.0012	26.16049	0.31	1.94
HV	Β	0.55	0.108899	5.114733	0.0000			

Table 7 presents the estimation of OLS to examine the impact of Realized Volatility (RV) on Historical Volatility (HV) yielded noteworthy results. The intercept coefficient, denoting the anticipated realized volatility when historical volatility is absent, was computed as 9.80. This coefficient demonstrated statistical significance ($p = 0.0012$), implying that there exists a fundamental level of realized volatility even in the absence of historical volatility. Additionally, the slope coefficient indicated a positive correlation between realized and historical volatility, with a one-unit increase in historical volatility resulting in a 0.55-unit increase in realized volatility. This correlation was highly significant ($p < 0.0001$), highlighting the predictive capability of historical volatility on realized volatility. The overall regression model was statistically significant, as shown by the F-statistic, and the R-squared value of 0.31 indicated that 31% of the variability in realized volatility could be elucidated by historical volatility. The Durbin-Watson statistic close to 2 suggested minimal autocorrelation in the residuals. Thus the null is rejected since $\beta1\neq0$. Yet, the historical volatility estimator demonstrates less explanatory power compared to the implied volatility estimator, as evidenced by the lower slope coefficient for historical volatility.

Table 8: Influence of Average Implied Volatility and Historical Volatility on Reliability Volatility
Equation: σ (RV) = α3+ β3 σ (IV) + λ σ (HV) + ε

Independent		Coefficient	Standard Error	t-statistic	Probability Value	F-Stat	R^2	DW
	α	4.073	3.850580	1.057972	0.2945	16.25	0.36	1.844
AVG_IV	β	0.715	0.330674	2.163600	0.0347			
HV	λ	0.035	0.263142	0.134935	0.8931			

Table 8 presents the estimation results for average implied volatility (AVG_IV) and historical volatility (HV) on realized volatility using ordinary least squares (OLS). The intercept coefficient, which represents the expected value of the dependent variable when AVG_IV and HV are zero, was estimated at 4.073, although it was not statistically significant at conventional levels (p = 0.2945). The overall regression model was statistically significant, supported by an F-statistic of 16.25. Furthermore, the R-squared value of 0.36 indicates that approximately 36% of the variability in the dependent variable can be explained by AVG_IV and HV. The detailed regression analysis reveals that only the slope coefficient of implied volatility is statistically significant, while the intercept term and the coefficient of historical volatility are not statistically significant, suggesting they are effectively zero. This implies that implied volatility captures all the relevant information found in historical volatility, and including historical volatility does not improve the model's explanatory power, as evidenced by the lack of improvement in the R-squared value. In fact, the inclusion of historical volatility reduces the slope coefficient of implied volatility from 0.75 to 0.71, indicating a downward adjustment. This reduction in the slope coefficient suggests a weakening association between implied volatility and the dependent variable when historical volatility is included in the regression. It suggests that historical volatility may introduce noise or conflicting signals, diminishing the estimated impact of implied volatility. Similarly, the decrease in the slope coefficient of historical volatility also indicates reduced explanatory power, suggesting that historical volatility becomes less effective in explaining the variability in the dependent variable when considered alongside implied volatility.

Implications of the Study

The implications of this study are multifaceted and provide valuable insights for both academia and practitioners in the financial markets. For traders, particularly those involved in the Indian options market and dealing with Bank Nifty index options, the study offers valuable guidance by assessing the efficiency of implied volatility in forecasting realized return volatility. A recent study by SEBI indicated that 90% of the traders lose money in the F&O markets (SEBI, 2023) (24). This could be partially attributed to the use of inefficient metrics and strategies to trade the markets. Out study proves the significance and inefficiency of one such metric (historical volatility) and establishes that forward-looking estimators such as implied volatility are much more efficient in predictive power when compared to historical and backward-looking volatility estimators. This calls for traders to look upon such forward-looking estimators when basing their trading decisions. For instance, in periods where IV tends to overestimate realized volatility, traders may implement strategies like Iron Condors to profit from potentially inflated option premiums when expecting stable price ranges. Conversely, during volatile market conditions where IV accurately predicts realized volatility, strategies such as Long Straddles can be employed to capitalize on anticipated price movements regardless of direction. Additionally, around earnings announcements where IV often increases, traders may utilize straddles or Strangles to benefit from expected volatility expansions. Furthermore, strategies like Protective Puts may be employed as insurance against downside risk, particularly if IV underestimates realized volatility during market uncertainty or downturns. The findings of our study also reveal about the ability of the Indian financial markets to price assets efficiently. It is often debated that assets require a substantial amount of time to be priced correctly and that price discovery is long-term process. However, market efficiency reveals itself in often under-looked areas such as this. The ability of an implied volatility estimator in shortlived assets such as the monthly options prove that even in shorter time horizons, markets price assets efficiently. This can be further extrapolated and serve as a basis for academicians to research further on forward looking and implied metrics such as the implied volatility, and implied equity risk premiums, to test the efficiency of Indian markets further on. The study also suggests the use of market- based, real time and dynamic metrics to be inputted into the risk models and decisions of institutions such as hedge funds when pricing assets using valuation techniques rather than depending on historical variables which prove to be less significant and contain less information. For instance, in a standard DCF model, the conventional usage of historical risk premiums can be replaced using implied risk premiums for better price discovery of the security since it results in a more accurate cost of equity supported by the implied estimator rather than a historic one. The study, also proves a basis that, the India VIX (Volatility index) which is calculated using the implied volatility of live option prices, must also be efficient in terms of its predictive ability to forecast volatility. This index is vastly used by traders and Institutions to get a broad idea about the future volatility in the markets. Our study further supports the efficiency of this index. By aligning their options trading strategies with insights from our study on IV efficiency, traders can aim to optimize their profitability and risk management strategies in the financial markets. Practitioners, such as risk managers within financial institutions or trading firms, can leverage the research findings to refine risk assessment models, develop robust hedging strategies, and enhance overall risk management practices.

Conclusion

In conclusion, the lack of research and contradicting findings on the efficiency of the implied volatility estimate in the context of Indian markets, calls for further research in the topic. Moreover, the absolute absence of research in studying the bank nifty index options, and the informational efficiency of their prices despite it being one of the widely traded Indian indices under the F&O segment begs the question of the accuracy of these forecast estimators such as implied volatility. With our results, the study finds implied volatility as an efficient forecaster of the realised volatility with a significant slope co-efficient of 0.75 as inferred from the prices of at-the money options. This is in line with the results of the study prior conducted that examined at-the money options using implied standard deviation, affirming that they largely incorporate pertinent information into their pricing (1). By combing the information of IV from both call and put options, the findings of the study exhibit similar results to the study, where the relationship between implied and realized volatility in Danish at-the-money call and put options based on was examined and it was concluded that implied volatility embedded in call and put options efficiently predicts realized return volatility (9). In specific to the Indian markets, this study aligns with the findings of prior researches conducted which also concluded that implied volatility serves as an unbiased and efficient predictor of realized volatility, outperforming historical volatility (13, 14). Our results suggests that historical volatility does not add more predictive power when regressed along with implied volatility and proves to be a very inefficient predictor of realised volatility. This conclusion has similar results with the research findings of the study conducted which revealed that models incorporating implied volatility as an explanatory variable achieved the highest regres1sion R-squared values, underscoring the efficiency of implied volatility in its predictive power over historical volatility (11). The result of this study contradicts the results of the study conducted, which suggested that implied volatility tends to underestimate realized variance and also contrasts with the findings of prior research conducted, which concluded that the implied volatility on one-month call options on CNX Nifty did not explain realised volatility as effectively as historical volatility (18, 21). Thus, the study adds more evidence and arguments to the side of the spectrum which argues that implied volatility is a reliable metric to forecast future volatility as previously put forward by the researchers and will help options traders make better and data-driven judgements.

Limitations and Scope for Future Research

It is important to emphasize that this study's findings are specific to Bank Nifty options and may not generalize to the entire Indian options market. Further research focusing on other major indices like the Nifty 50 is necessary to fully assess the efficiency of implied volatility (IV). The study assumes a uniform impact of holidays across all data points and covers a five-year period from December 2017 to December 2022. Future studies could extend this timeframe to evaluate longer-term influences. Moreover, potential market disruptions or anomalies during the data collection period, which could impact the reliability of findings, were not considered. The assumption of a consistent relationship between implied and realized volatility over the study period may not hold in dynamic market conditions. Additionally, the calculation of implied volatility is based on the Black-Scholes model, which relies on certain market behaviour assumptions that may not always align with real-world conditions. Furthermore, the study overlooks transaction costs, which could affect the profitability of trading strategies relying on implied volatility forecasts. Therefore, while these insights shed light on the predictive ability of implied volatility for Bank Nifty options, caution is advised in applying these results broadly to other markets or time periods without additional rigorous analysis. Looking ahead, future research could explore additional factors influencing implied volatility efficiency, such as market microstructure dynamics, investor sentiment, and regulatory changes. Extending the analysis to other major indices within the Indian market would provide a more comprehensive view of implied volatility's predictive capabilities. Additionally, extending the study duration would offer insights into its longer-term impacts.

Abbreviation

Nil.

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Author Contributions

Dr. John Paul Raj and Sam: Contributed to the introduction and literature review for the research. Dr. Sathish P and Deepika: Contributed to the methodology and analysis part. Dr. Saravanan: Contributed to the conclusion and implications of the research.

Conflict of Interest

The authors declare that there are no conflicts of interest regarding the publication of this manuscript we confirm that the research was conducted with utmost integrity and without any undue influence.

Ethics Approval

Not applicable.

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References

1. Beckers S. Standard deviations implied in option prices as predictors of future stock price variability. Journal of Banking & Finance. 1981;5(3):363-81.
2. Hull J, White A. Optimal delta hedging for options. Journal of Banking & Finance. 2017;82:180-90.
3. Hansen PR, Lunde A. Realized variance and market microstructure noise. Journal of Business & Economic Statistics. 2006;24(2):127-61.
4. Black F, Jensen MC, Scholes M. The capital asset pricing model: Some empirical tests. Studies in the Theory of Capital Markets. 1972;23(1):1-54.
5. Latane HA, Rendleman RJ. Standard deviations of stock price ratios implied in option prices. The Journal of Finance. 1976;31(2):369-81.
6. Day TE, Lewis CM. Stock market volatility and the information content of stock index options. Journal of Econometrics. 1992;52(1-2):267-87.
7. Whaley RE. Valuation of American call options on dividend-paying stocks: Empirical tests. Journal of Financial Economics. 1982;10(1):29-58.
8. Jorion P. Predicting volatility in the foreign exchange market. The Journal of Finance. 1995;50(2):507-28.
9. Strunk Hansen C. The relation between implied and realised volatility in the Danish option and equity markets. Accounting & Finance. 2001;41(3):197-228.
10. Christensen BJ, Prabhala NR. The relation between implied and realized volatility. Journal of financial economics. 1998;50(2):125-50.
11. Corrado CJ, Miller Jr TW. The forecast quality of CBOE implied volatility indexes. Journal of Futures Markets: Futures, Options, and Other Derivative Products. 2005;25(4):339-73.
12. Bakanova, M. The impact of economic news on financial markets. International Journal of Financial Economics. 2010;5(2);97–110.
13. Kumar SSS. Intraday information efficiency in Indian stock index options market. Journal of Emerging Market Finance. 2008; 7(3);241–262.
14. Padhi P, Shaikh I. Pricing efficiency in the index options market. Decision. 2013;40(3);175–187.
15. Gemmill G. The Forecasting Performance of Stock Options on The London Traded Options Market. Journal of Business Finance & Accounting. 1986 ;13(4):535-46.
16. Canina L, Figlewski S. The informational content of implied volatility. The Review of Financial Studies. 1993;6(3):659-681.

17. Jackwerth JC, Rubinstein M. Recovering probability distributions from option prices. The Journal of Finance. 1996;51(5):1611-31.
18. Lamoureux CG, Lastrapes WD. Forecasting stock-return variance: Toward an understanding of stochastic implied volatilities. The Review of Financial Studies. 1993;6(2):293-326.
19. Becker R, Clements AE, White SI. Does implied volatility provide any information beyond that captured in model-based volatility forecasts?Journal of Banking & Finance. 2007;31(8):2535-49.
20. Li S, Yang Q. A comparison of long-term forecast accuracy between ARCH and GARCH models for S&P 500 index returns. Applied Economics Letters. 2008 ;15(9):683–688.
21. Inder S. A study on the forecasting ability of implied volatility. The European Journal of Finance. 2016 ;22(9):666–689.
22. https://www.niftyindices.com/reports/index842 factsheet
23. Szakmary A, Ors E, Kim JK, Davidson III WN. The predictive power of implied volatility: Evidence from 35 futures markets. Journal of Banking & Finance. 2003;27(11):2151-75.
24. https://www.sebi.gov.in/reports-andstatistics/research/jan-2023/study-analysis-of-profit-and-loss-of-individual-traders-dealing-in-equity-fando-segment_67525.html