

A Review of Methods for Predicting Stock Volatility: A Comparison of Traditional Econometric Models, Implied Volatility, and Machine Learning Methods

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Abstract

Stock volatility forecasting serves as a crucial underpinning for derivatives pricing, asset allocation, and risk management. This paper examines volatility proxy variables, empirical applications, as well as forecasting evaluation metrics, and then reviews representative models and empirical evidence across three research pathways. The comparison concerns the information basis and forecasting horizon, taking into account explanatory power, stability, and economic value. A comprehensive review of the literature suggests that traditional models remain a robust benchmark in scenarios with limited data, in which emphasis is placed on interpretability and reproducibility. Implied volatility can provide incremental information beyond historical data; however, its predictive power is influenced by variance risk premiums, liquidity, and maturity matching. Machine learning offers greater flexibility in high-dimensional data environments, but its advantages depend on rigorous time-series validation and control of information leakage. Because of inconsistencies in proxy variables, loss functions, sample partitioning, and market conditions, existing evidence fails to support the universal superiority of any single method across all tasks. Future analysis should conduct cross-market tests under a unified evaluation framework and integrate statistical forecasting accuracy with economic value in risk management and investment decision-making.

Keywords

volatility forecasting, GARCH-type models, implied volatility, machine learning, model comparison

1. Introduction

The extent of stock volatility is an indicator of the uncertainty that characterizes asset price changes and is an important input to derivatives pricing, asset allocation, and risk management [1]. Volatility is not directly observable and has clustering, persistence, long memory, and asymmetry. The factors that affect its fluctuations include market conditions, economic uncertainty, and investor sentiment [2, 3, 4]. To forecast volatility, it is necessary to identify its historical dynamics and determine the horizons and market conditions under which different types of information provide incremental value.

The study of this question has been divided into three general directions. To begin with, conventional econometric models extract the volatility pattern based on historical returns, the range of prices, and high-frequency realized measures, and make use of structures like GARCH, HAR, Realized GARCH, and CARR

to identify persistence and component differences [4, 5, 6, 7, 8, 9, 10]. Second, implied volatility techniques use option prices, variance risk premiums, and trading volume to infer what markets expect the future volatility to be [11, 12, 13, 14]. Third, machine-learning methods combine high-frequency variables, cross-asset correlations, and text sentiment into an integrated prediction model to find high-dimensional and nonlinear associations [2, 15]. The three approaches focus on the historical realized information, market forward-looking information, and the capability to handle multi-source information, respectively.

In the current literature, the key issue being contested is whether a model's predictive advantage persists under a common evaluation framework. The selection of true volatility proxies and loss measures, the forecast horizon, information timing, and sample partitioning influence the ranking of models [16, 17, 18]. In addition, a decrease in statistical error may not be translated to economic benefit in risk management or investment decision making [19]. The main topic of this paper is information sources, with an initial discussion on volatility measures, their applications, and evaluation, followed by a systematic review of the three categories of methods. The applicability conditions and controversies of each method are compared and contrasted in order to draw comparisons between them and outline the gaps in research and future testing opportunities.

2. Measurement, Applications, and Evaluation of Volatility

The comparability of various studies is only possible if the predicted objects and assessment criteria are more or less similar. In this section, the commonly used proxy variables of volatility, applications of forecasting outcomes in derivatives pricing and risk management, and out-of-sample loss functions and model comparison tests will be discussed in sequence.

2.1 Volatility Proxies and Measurement Differences

The most popular proxy variables are squared returns, price range, and realized volatility. Squared returns depend exclusively on adjacent closing prices; they are widely available over long historical periods but are highly noisy at the daily frequency. Price range involves the use of both high and low prices that strike a balance between cost of the data and intraday information content [5, 20]. Realized volatility, however, summarizes intraday high-frequency returns and can better characterize price paths, although it is vulnerable to bid-ask spreads, asynchronous trading, and sampling frequency [8, 20]. The errors in measurement of these three forms of proxy variables vary, and an identical prediction would be ranked differently with various loss functions. Comparisons across studies thus need standardization of proxy variables or adoption of evaluation procedures that are less sensitive to proxy errors [18].

2.2 Empirical Applications of Volatility Forecasting

The value of volatility forecasting is ultimately reflected in specific financial decision-making. Firstly, in the pricing of an option, projected volatility has a direct implication on theoretical prices and risk exposure estimates. To illustrate, in the case of SSE 50 ETF options, model-free implied volatility combines information on various strike prices, and incorporates forward-looking information, not just historical volatility. As there is a variance risk premium between risk-neutral expectations and realised volatility, correcting this risk premium in implied volatility is likely to decrease the forecast bias [11, 12, 14]. In this context, the difference between the expected volatility and the risk compensation will also influence the forecast accuracy.

Secondly, in market risk management, the forecasting of volatility can be viewed as an important input in the calculation of Value at Risk (VaR) and determining capital buffers. Wu Xinyu et al. [19] included both options information and high-frequency data in the VaR measures; the findings indicated that the combination of forward-looking information with the recent realized volatilities would contribute positively to the characterization of risks in extreme market situations. The applications of VaR pay attention to the identification of tail losses as well as the evaluation of the appropriateness of the risk coverage, which makes it possible to test how statistical accuracy can be transformed into economic and managerial value. In considering the assessment of volatility models, the forecasting problem and its duration must be considered in the analysis together with the decision-making loss function.

2.3 Out-of-Sample Evaluation and Model Comparison Tests

The in-sample fitting performance cannot be used to measure a model's predictive power out-of-sample. In order to make the comparison results reliable, related research generally splits the data into training and testing intervals chronologically and uses rolling or extended windows to mimic the real-life process of the information being received over time [1, 15, 16]. Selection of evaluation metrics also affects the findings of model comparisons. Mean Squared Error (MSE) emphasizes measuring absolute error, but robust loss functions like QLIKE are able to decrease the effect of measurement errors of proxy variables on model rankings [18]. For predictive-accuracy testing, the Diebold-Mariano test [21] is commonly used to determine whether the difference between the forecast errors of two models is statistically significant. Giacomini and White [22] extended forecast evaluation to conditional predictive ability while accounting for parameter-estimation uncertainty. When comparing a number of models simultaneously, Hansen et al. [17] suggested using the Model Confidence Set (MCS) to determine a set of statistically indistinguishable superior models, which precludes the misinterpretation of small or random model error differences as stable predictive benefits.

3. Traditional Econometric Models Based on Historical Information

The traditional econometric model has been developed over time in the direction of the introduction of intraday, long-term, and state information on the basis of historical price dynamics. These types of models also have a well-defined structure, simple interpretation of parameters, and are relatively easy to reproduce; they can be used as the foundation of volatility prediction and as the standard to compare more advanced techniques [1].

3.1 ARCH and GARCH: Volatility Clustering and Persistence

Engle [10] suggested using the ARCH model to express conditional variance as a function of the squares of previous shocks, which introduces volatility clustering to a statistically estimateable form. Bollerslev [9] also added the lagged conditional variance term to the GARCH model in order to portray volatility persistence with fewer parameters. Both model classes require only daily returns and can thus be used in situations with low data frequency or when interpretability of the parameters is important. Nonetheless, they have mostly been constrained in terms of information to historical returns, such that it is challenging to directly use intraday price paths or consider option expectations and textual information. Subsequent developments have therefore focused on incorporating these additional sources of information.

3.2 Realized GARCH and HAR: High-Frequency Information and Long Memory

Realized measures can be directly constructed by the use of high-frequency data and intraday information may be included in conditional volatility models. Realized GARCH links daily returns, latent conditional variance, and realized volatility through a measurement equation. Research on the Chinese market has shown that such a framework enhances out-of-sample predictions of the CSI 300 Index [7, 23]. The HAR model is based on the approximation of the long-memory properties of volatility with daily, weekly, and monthly factors; it has a simple form that can be extended to include jumps and other high-frequency factors [8, 15]. According to cross-market evidence, nonlinear or very complex models do not always outperform linear benchmarks over all horizons [16]. Efficiency of high-frequency information is determined by sampling noise, model structure, and forecast horizon.

3.3 CARR, Component Decomposition, and Macro Information

In contrast to models based on closing returns, CARR directly captures the price range created by the high and low prices, thereby retaining part of the intraday information at a relatively low data cost [5, 20]. On the basis of this, score-driven CARR models will reflect conditional heteroscedasticity through dynamic parameter updates, whereas multiplicative CARR will incorporate long-term, short-term, and high-frequency measures [5, 6]. Another group of studies breaks down volatility into direction, magnitude, long-term trends, and market states. Quantile decomposition and state transitions have been found to be able to differentiate between times of high and low volatility [4]. Economic uncertainty direction and cycle impact long-term volatility in an asymmetric way [3]. Although these models are more interpretable economically, the low frequency and

publication lags of macroeconomic variables renders them more appropriate in complementing medium- to long-term prediction.

4. Implied Volatility Methods Based on Option Information

Implied volatility is based on market estimates of volatility until the end of a contract and can give a prediction of the future beyond past returns [1, 14]. Pricing assumptions, market frictions, and risk compensation also affect the price of options. As such, although implied volatility is forward-looking, it might not necessarily be an unbiased predictor of future actual volatility.

4.1 Additional Information Provided by Implied Volatility

Implied volatility based on the traditional Black-Scholes (BS) is based upon certain pricing models and individual option quotes. Model-free implied volatility aggregates information across multiple strike prices, thereby reducing reliance on the assumptions of any particular pricing model. Evidence based on the SSE 50 ETF options suggests that the model-free implied volatility reflects the information provided by the traditional BS implied volatility and much of the historical volatility information [11]. In their research on the options of the S&P 500 index, Jiang and Tian [24] discovered that model-free implied volatility contains information on both Black-Scholes implied volatility and historical realized volatility, and is more efficient in forecasting future volatility. Yet, its performance also depends on whether the quality of the quote, market liquidity, and forecast horizon are well-fitted [24]. Implied volatility measurements can have a significant level of noise when contracts are rarely traded, strike price distributions are scarce, or bid-ask spreads are large.

4.2 Variance Risk Premium and Forecasting Bias

The implied variance is made up of the expectations of future volatility and the compensation that investors require to cover the volatility risk; therefore, predicted and observed volatility are not entirely consistent with a risk-neutral measure [12, 14]. Studies by Bollerslev et al. [25] suggest that the variance risk premium, defined as the difference between model-free implied variance and realized variance, has asset pricing information and this also implies that implied measures have risk neutral estimates as well as compensating risk. Studies of the Chinese options market have shown that predictive and pricing information is present in the variance risk premium itself; detecting and controlling such a premium can help in eliminating the prediction bias of the implied volatility [11, 12]. The implied volatility forecast error can be due to the market expectation bias, risk compensation, as well as liquidity and quotation frictions.

4.3 Supplementary Insights from Options Trading Volume and High-Frequency Information

Besides the price, the volume of options trading also indicates what kind of contracts are of interest to information traders. Ni et al. [26] discovered that the net demand for volatility by non-market makers within the options market is a predictor of the future realized volatility of the underlying stock, meaning that trading activity may give volatility information without the need for option prices. Research on the SSE 50 ETF options indicates that the prediction ability of HAR-type models can be enhanced by trading volume in deeply out-of-the-money options and that the direction of the effect varies across call and put trading volumes [13]. Option prices are indicative of market expectations, high-frequency volatility indicates recent factual volatility, and trading volume describes trading activity. The joint application of this data may increase the amount of information available to risk models [11, 19]. The independent incremental value of each of the variables should be determined by nested comparisons or ablation tests.

5. Machine Learning Methods Based on Multi-Source Data

The main application of machine learning is to filter and integrate high-dimensional variables and to capture underlying nonlinear connections. Their predictive benefits are then dependent on the quality of data, feature engineering, and validation plan.

5.1 Integration of High-Dimensional Nonlinear Relationships and Har

Sparse variable selection can be done through lasso, random forests can do it by identifying nonlinearities and variable interactions, and neural networks can do it as they can fit complex time dependencies. Current studies usually integrate such methods with the help of the HAR structures to increase the functionality of feature processing but still maintain the daily, weekly, and monthly memory features. Research on Chinese high-frequency data shows that jump components, variable selection, and nonlinear fitting may enhance out-of-sample predictions of certain samples [15]. The GAT-TCN model suggested by Lü Chengshuang et al. [2] considers both stock correlations and time dependencies at the same time. There was no systematic evidence that all nonlinear models were better than other models at all time horizons when comparing global stock indices [16]. Complexity of the models might imply predictive benefits only in the case that the incremental information is stable and the sample size is large enough.

5.2 Text Sentiment and Macroeconomic Uncertainty

Text and macroeconomic variables increase the information edge of volatility prediction. Lü Chengshuang et al. [2] used fine-tuned large language models to transform the text of the stock forum into sentiment indicators that were used as inputs to a forecasting network, along with price and technical features. In their ablation results, they found that sentiment information provides incremental predictive value in the specific stock sample. Uncertainty in the economy is studied more extensively in relation to long-term volatility and its variation in direction and cycles [3], whereas higher frequency price variables are mainly used to make shorter term predictions [15]. This finding indicates that various information sources can be associated with various time scales, but the most effective way to combine information from multiple sources remains unclear.

5.3 Overfitting, Information Leakage, and Reproducibility

The credibility of machine-learning results depends critically on the validation procedure. Financial data is highly time-ordered. Randomly splitting the sample or conducting standardization, variable selection, and hyperparameter selection on all samples will permit future information to creep into the training process. In-sample fit could also merely indicate the memory of historical noise [2, 15]. Comparisons of models must be based on out-of-sample validation using chronological rolling updates and must be compared with simple benchmarks under the same information set, forecast horizon, and loss function. The statistical measures like MCS can also be used to check if the errors differ more than sampling variation [17, 18]. Until there are simple models competing at the level of the best-performing models, it cannot be stated that complex models have a steady advantage [16].

6. Comparison and Synthesis of Three Classes of Volatility Forecasting Methods

These three methods have significant differences between them on the basis of their information foundation and processing techniques. Table 1 shows the information sources and representative methods of every category and compares them based on their key advantages, limitations, and areas of application. Traditional econometric models perform well in terms of low data requirements and interpretability; implied volatility derives its main value from the market's forward-looking information; and machine learning provides more flexibility when working with multi-source and high-dimensional systems and nonlinear systems. All three methods are also limited by historical information lags, risk premium, liquidity, and the risks of overfitting and high reproducibility costs.

6.1 Information Sources, Forecast Horizon, and Market Conditions

The questions that a model can answer depend on its information sources. The historical returns and the realized measures are well-suited to describe past dynamics in volatility. Multi-source variables might reflect sentiment and correlation structures that cannot be accounted for by prices, and option prices reflect market expectations associated with the maturity of the contract [1, 2, 14, 15]. There is also the impact of the forecast horizon on the comparative strength of different approaches. Intraday price and jump terms are mostly useful in predicting short-term movements, whereas macroeconomic uncertainty and long-term terms are more appropriate to explain mid- to long-term movements; option data is affected by time to maturity [3, 4, 8, 13]. Straightforward linear models could be competitive in quiet times because the parameters are stable, but in

times of high volatility or structural change, state transitions, asymmetric shocks, and sentiment information may play a more significant role. One of the reasons that generalization of the model rankings is hard to achieve is because the existing research has not developed a systematic categorization of the above conditions.

Table 1: Comparison of Three Types of Volatility Forecasting Methods

Comparison Dimensions	Traditional Econometric Models	Implied Volatility Methods	Machine Learning Methods
Data Sources	Historical returns, price ranges, and realized measures	Option prices, trading volume, and variance risk premiums	High-frequency variables, cross-asset correlations, and text sentiment
Representative Methods	GARCH, HAR, Realized GARCH, CARR	BS Implied Volatility, Model-Free Implied Volatility	Lasso, Random Forests, Neural Networks, GAT-TCN
Key Advantages	Clear structure, easy to interpret and reproduce, with low data requirements	Forward-looking, providing market expectations beyond historical information	Capable of filtering high-dimensional variables and fitting nonlinear relationships
Key Limitations	Difficulty in directly incorporating external information such as options and text	Susceptible to the effects of risk premiums, liquidity, quote noise, and maturity mismatches	Risks of overfitting, information leakage, and insufficient interpretability
Applicable Conditions	Limited data or a focus on mechanism-based explanations and robust benchmarks	Active options markets with reliable quotes and maturity matching	Adequate multi-source data and rigorous validation procedures

6.2 The Trade-off Between Explanatory Power, Forward-Looking Nature, and Flexibility

Traditional econometric model parameter structures can assist in explaining the causes of volatility persistence, but when structural constraints are strong, they might prevent new information from being considered. Implied volatility is forward-looking but needs a disentanglement between actual expectations, risk premium, and market frictions. Machine learning minimizes limitations on functional forms yet raises data demands, parameter-tuning difficulties and reproducibility costs, [1, 11, 12, 15, 16]. The selection of methods must be based on the goals of research. The mechanism-based explanation needs an identifiable parameter structure, and the extraction of short-term market expectations depends on the quality of options data, whereas high-dimensional forecasts need strict out-of-sample validation.

6.3 Unified Evaluation and Integrated Research

To achieve a proper comparison, there are at least four standardized conditions necessary, that is, the volatility proxy variables, the cutoff point concerning forecast information, the forecast horizon, and the out-of-sample loss function [16, 17, 18]. The statistical and economic assessments need to be reported concurrently. A lower error indicates that the forecast is closer to the proxy variable. The economic worth of a model needs to be evaluated on the basis of observable changes in option pricing, VaR coverage, or investment decisions [16, 19]. Some of the studies on integration have gone beyond the limits of these three methodological groups, such as integrating machine learning into HAR models or using options and high-frequency data to measure risks together [15, 19]. The future comparisons ought to aim at determining what kinds of information can give steady incremental benefits depending on what conditions prevail. Following this, Table 2 presents representative models in terms of their research role, depicting the relationship between dynamic nature of volatility, extraction of information on its future behavior, and combination of various sources of information with statistical analysis.

Table 2: Functional Chains and Representative Methods in Volatility Forecasting Research

Research Function	Representative Models or Metrics	Primary Information	Applicable Problems
Daily Volatility Dynamics	ARCH, GARCH	Historical Returns and Lagged Conditional Variance	Volatility Clustering, Persistence, and Benchmark Forecasts
High-Frequency and Long-Memory	Realized GARCH, HAR	Realized Measures and Daily, Weekly, and Monthly Components	Short- and Medium-Term Forecasting and High-Frequency Information Gains

Research Function	Representative Models or Metrics	Primary Information	Applicable Problems
Range and Component Decomposition	CARR, quasi-score-driven, and multiplicative component models	Price Range, Long-Term and Short-Term Components	Utilization of intraday information under data cost constraints
Forward-Looking Expectations	BS Implied Volatility, Model-Free Implied Volatility	Option Price Cross-Sections	Term-Matched Expectations of Future Volatility
Risk Compensation and Trading Activity	Variance Risk Premium, Option Trading Volume	Risk-Neutral Expectations, Trading Volume	Bias Correction and Identification of Incremental Information
Multi-source Nonlinear Forecasting	HAR Fusion, GAT-TCN	High-frequency variables, correlation networks, and text sentiment	High-Dimensional Variable Screening and Nonlinear Fitting
Prediction Comparison	Robust Loss Functions, MCS	Out-of-sample prediction loss	Reducing the Impact of Proxy Noise and Testing Ranking Stability

7. Conclusions and Future Directions

The paper presents three research directions in the field of stock volatility prediction according to the information sources. According to current knowledge, traditional econometric models have relative strengths in their ability to explain structures, implied volatility provides forward-looking market information, and machine learning has a comparative advantage in its ability to process high-dimensional information. The constraints of these advantages include the quality of the data, forecast time scales, the state of the market, and validation plans. The performance of models is highly conditional, and the discrepancies in the outcomes of studies are frequently more effectively accounted for by the source of the information and the structure of the assessments than by the complexity of the models.

There are four remaining drawbacks in the current literature. First, most empirical researches conducted domestically focuses on the CSI 300 Index, the SSE 50 ETF options, or particular phases of the market. Their findings are not sufficiently supported by evidence that suggests they could be applied to different markets, assets, and extreme market conditions. Second, various studies use different proxies of volatilities and loss functions, and information timing, forecasting windows, and division of samples differ greatly. The performance of the model can be due to both methodological differences and differences in the research design. Third, while many studies rely primarily on statistical forecast errors, joint tests of economic value—such as option pricing, VaR coverage, and investment decisions—remain insufficient. Fourth, there is no consensus on whether machine learning can consistently outperform simple linear models. Existing research also rarely systematically decomposes whether improvements stem from new information, variable selection, or nonlinear structures.

These shortcomings may be addressed by conducting future research in three directions. Initially, proxy measures, cut-off points of information, forecast horizons, and rolling out-of-sample strategies need to be standardized. Based on this, comparative studies of various markets, asset types, and levels of volatility ought to be carried out, and report both forecast inaccuracies as well as their uncertainty. Then, statistical precision and economic worth must be considered as part of one assessment system to assess if improvement of forecasts may always decrease the error in option pricing, improve the coverage of VaR, or raise the returns adjusted to risks. Lastly, multi-source integration studies involve both ablation tests and time-series validation. It is necessary to determine the independent incremental value of high-frequency, option, macroeconomic, and text-based information that will help define the applicability limits of more complicated models in comparison with simple ones.

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