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Advanced Approaches to Volatility Forecasting: A GARCH-Based Optimization Framework

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Abstract. Volatility forecasting is crucial for option pricing and financial risk management. Existing research can be categorized into two main types: parametric and non-parametric models. Research has concluded that non-parametric models enhance prediction accuracy by integrating high-frequency data or implied volatility while the integration requires more precise data and consumes more time. On the other hand, parametric modules such as Generalized Autoregressive Conditional Heteroskedasticity (GARCH) and its derived models are adept at capturing volatility clustering, but heavily rely on historical data and tend to lag in their response to new information. This review proposes an optimized Exponentially Weighted Moving Average GARCH (EWMA-GARCH) model to neutralize the insensitivity in existing studies, such as GARCH models' ineffective integration of IV and incomplete model comparisons. This study provides a theoretical framework by incorporating IV into the GARCH residual term using an EWMA-weighted form with an exponential decay mechanism to assign higher weights to recent IV, while maintaining the core structure of GARCH to capture volatility clustering. Future prospects include segmenting IV by time scales, incorporating external risk factors, customizing parameters for different markets, and enhancing extreme risk prediction through quantile regression. Thus, it integrates forward-looking IV into GARCH models and offers practical risk management guidance.

Keywords: Volatility forecasting, GARCH, EWMA, EWMA-GARCH

1. Introduction

Option pricing is considered the foundation of modern portfolio theory, and volatility is the key factor to realize the theoretical model [1-3]. Current research in volatility forecasting has two main strands. Parametric models like GARCH and EGARCH capture volatility clustering but rely on historical data and lag in responding to new information. Non-parametric models such as HAR, RECH, and artificial neural networks integrate high-frequency data or implied volatility to improve accuracy, with implied volatility enhancing forecasts significantly. However, gaps exist: GARCH models rarely integrate implied volatility effectively. Model comparisons lack mainstream alternatives; Parameters ignore asset characteristics [4-6].

To address these issues and advance the theoretical framework of volatility computation, this paper proposes an optimized EWMA-GARCH model. The research focuses on integrating implied

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volatility into the GARCH model via an exponentially weighted moving average (EWMA) mechanism while retaining the model's ability to capture volatility clustering. The study also explores optimal parameter settings for the optimized model across different assets and evaluates its performance against other mainstream volatility forecasting models.

This method assumes the GARCH residual term modified to an EWMA-weighted form that incorporates implied volatility, resulting in the derivation of the EWMA-GARCH model formula. Empirically, financial market data are used to estimate model parameters, and performance is evaluated using metrics like R-squared, Mean Squared Error, and Quasi-Likelihood [2,5,7]. The hypothesis is to integrate implied volatility via an exponentially weighted moving average mechanism while retaining GARCH's ability of clustering effects, though it remains a prototype needing further real-data backup considering diverse market conditions among countries.

This study contributes to volatility quantification by providing an implied volatility-integrated GARCH framework, offering parameter adaptation suggestions, and guiding risk management. It also lays a foundation for subsequent empirical validation and model optimization, promoting the development of volatility forecasting theories.

2. GARCH derived models

2.1. Volatility and the GARCH model

Volatility describes the degree of fluctuation in the price of financial assets. It serves as a measure of asset return's uncertainty and reflects the risk level of financial assets. In volatility calculation, the choice between emphasizing historical influences or current market shocks exerts a profound impact on the quality of data fitting.

The Generalized Autoregressive Conditional Heteroskedasticity mode computes historical volatility with an emphasis on volatility clustering—a key stylized fact in financial markets where large price movements tend to be followed by further large movements [4,6]. The model incorporates persistency and shocks of the volatility with lagged conditional variance and lagged squared residuals respectively, so that the model can capture time-varying volatility dynamics more accurately. The most widely used specification, GARCH(1,1), takes only one lag for both past volatility and residual terms [7]:

$$\sigma_t^2=\alpha_0+\mu\epsilon_{t-i}^2+(1-\mu)\sigma_{t-i}^2 \tag{1}$$

Where α_0 composes the long-term mean level, μ and (1-μ) respectively demonstrates the short-term impact factors of shock and clusters altogether with lag 1 unexpected volatility and historic volatility source.

This structure directly maps to the "volatility clustering" property highlighted in pricing models relying on Markov chain approximations. The GARCH model computes historic volatility with an essence to aim on volatility clustering. It also introduces the residual term to detect current shocks. GARCH concludes a referenced HV used for pricing via the Black-Scholes formula. But as described above, the method has a short-time bias and over-restricts calibrations [2,7]. Specifically, its reliance on fixed lag structures limits flexibility in adapting to rapidly changing market conditions—unlike Markov chain-based approximations that adjust state transitions dynamically. This rigidity explains why GARCH model underperforms 100-day historical volatility in Black-Scholes applications for S&P 500 options [2].

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2.2. E-GARCH model

The Exponential Generalized Autoregressive Conditional Heteroskedasticity model, introduced by Nelson outperforms the traditional GARCH model by addressing two key limitations: the symmetric reaction toward positive and negative shocks and the requirement for non-negative parameters. GARCH model assumes that volatility reacts symmetrically to positive and negative shocks, which is inadequate in capturing the leverage effect in financial markets. In contrast, EGARCH eliminates this deficiency by allowing for asymmetric responses of volatility to different shocks, expressing the conditional variance in the form of a natural logarithm. This logarithmic specification enables EGARCH to capture the asymmetric impact of shocks on volatility, where parameter γ in the model can reflect the difference in the effect of positive and negative shocks: a significant negative γ indicates that negative shocks amplify volatility more than positive shocks, consistent with the stylized fact of leverage effects observed in equity markets. This can also be implied by Markov chain models that incorporate state-dependent volatility regimes [4].

Moreover, the logarithmic form of the EGARCH model relaxes the parameter restriction of non-negative variance in original GARCH model [3,5,8]. This enhancement makes the model more flexible in fitting the actual characteristics of financial time series and avoids unreasonable results caused by forced non-negative constraints on parameters. For instance, during the pandemic, the traditional index exhibits a higher peak of estimated volatility compared to the ESG index. This empirical finding aligns with EGARCH’s strength in capturing extreme volatility spikes: its asymmetric term γ allows it to better absorb sudden negative shocks during pandemic-driven market crashes, compared to GARCH, which would underestimate volatility due to its symmetric weighting of shocks [8].

3. Optimizing volatility forecasting

3.1. EWMA weighting model

When dealing with data, particularly time series data, it is important to consider weighting based on time considerations. The most recent shock typically has the greatest impact, and factors that better represent market conditions, such as implied volatility and the stock lending volume, are more likely to follow a continuous-time Markov chain. GARCH derived models adhere to such logic with a clustering method. By using historical volatility and residual term to represent the trend and current shocks, the model is adaptable to multiple circumstances by changing the weight factors. In comparison, the EWMA model has a similar formula structure. The lack of long-term mean parameter meant that the model fits better when used to compute short-term volatility. Through an exponential decay mechanism, recent data have a greater impact on current volatility than distant data, with weights decreasing in a geometric progression over time [7].

3.2. Hypothesis on EWMA-GARCH

Although the traditional GARCH model can capture volatility clustering, it has significant limitations in practice.

The parameter estimation is complex, requiring iterative fitting of multiple lagged parameters. Coefficients of ARCH and GARCH terms can easily leads to low computational efficiency when processing high-frequency data or large-scale samples.

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The exhibited lag in responding to new market information. Its residual term relies on the cumulative effect of historical volatility, making it difficult to quickly reflect sudden shocks. Volatility mutations caused by political instability has difficulty in quantify estimation, especially in asymmetric market environments [1]. Moreover, the GARCH model only relies on historical price data and does not incorporate the market's forward-looking expectations of future volatility. Traditional GARCH models depend on historical price data to depict volatility, which easily overfits local patterns of historical fluctuations (such as short-term rules under specific market conditions) and leads to poor adaptability to new market dynamics. Implied volatility (IV), derived from option market transaction pricing, is essentially the collective expectation of investors on future asset fluctuations. Its information dimension includes forward-looking variables such as macro policies and market sentiment that are not covered by historical prices, which can effectively dilute the one-sidedness of relying solely on historical data and thus reduce overfitting risks. From the perspective of short-term forecasting, as mentioned earlier, the EWMA model adapts to short-term fluctuations through an exponential decay mechanism, while IV itself has the characteristic of "reflecting market expectations in advance". Integrating it into the GARCH residual term in the form of EWMA weighting can not only maintain the EWMA's sensitivity to recent information but also enable the model to quickly capture short-term sudden shocks (such as policy changes and liquidity mutations), making up for the defect that the traditional GARCH's fixed lag structure lags in responding to short-term new information. This complements the limitation of simple historical volatility, which only looks back at past data and has insufficient sensitivity in short-term forecasting, further enhancing the timeliness and accuracy of short-term volatility forecasting.

Traditional GARCH models rely on historical price data to characterize volatility and tend to have insufficient adaptability to new market dynamics due to overfitting local patterns of historical fluctuations (e.g., short-term rules under specific market conditions). In contrast, implied volatility (IV) is derived from trading pricing in the option market and essentially represents investors' collective expectations of future asset fluctuations. Its information dimension covers forward-looking variables such as macro policies and market sentiment that are not captured by historical prices, which can effectively dilute the one-sidedness of relying solely on historical data, thereby reducing the risk of overfitting.

From the perspective of short-term forecasting, as mentioned earlier, the EWMA model adapts to short-term volatility through an exponential decay mechanism. IV itself possesses the characteristic of "reflecting market expectations in advance". Integrating it into the GARCH residual term in the form of EWMA weighting not only maintains the EWMA's sensitivity to recent information but also enables the model to quickly capture short-term sudden shocks (e.g., policy changes, sudden liquidity fluctuations). This makes up for the defect of the traditional GARCH's fixed lag structure, which lags in responding to short-term new information—and complements the limitations of simple historical volatility (which only looks back at past data and has insufficient sensitivity in short-term forecasting), further enhancing the timeliness and accuracy of short-term volatility forecasting [2,5]. Therefore, structural optimization of the GARCH model is necessary to integrate the informational value of IV.

To address the above limitations, an Exponentially Weighted Moving Average (EWMA) mechanism is introduced to integrate IV, with the specific improvement path as follows:

$$\mathrm{IV}_t{}^2=\omega'+\alpha\epsilon_{\mathrm{wieghted}}{}^2+\beta\mathrm{IV}_{t-1}{}^2 \tag{2}$$

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The volatility update formula in the GARCH model, which is traditionally based on historical residuals, is modified to an EWMA form that incorporates IV.

$$\epsilon_{\text{wieghted}}{}^{2} = (1-\lambda)\sum_{i=0}^{k}\lambda^{i} \tag{3}$$

where λ is the decay factor (usually 0.94), assigning higher weights to recent IV to dynamically track market expectations.

On the other hand, the core structure of the GARCH model is retained to capture volatility clustering. Replacing traditional residual term with an EWMA-integrated IV maintains the depiction of historical volatility patterns while incorporating forward-looking information.

4. Limitation and future research directions

The EWMA-GARCH model has already demonstrated advantages in information completeness by integrating implied volatility. Future efforts can further expand information dimensions in several promising directions.

First, inspired by the Heterogeneous Autoregressive (HAR) model's approach to decomposition of short-, medium-, and long-term volatility, IV can be segmented into daily, weekly, and monthly components. Additionally, rough volatility models—known for capturing long-range dependence in volatility—can be combined with the EWMA weighting mechanism to refine the characterization of multi-scale volatility dynamics, especially for assets with persistent volatility patterns [6]. By assigning differentiated weights via EWMA, the model can better capture the distinct dynamics of volatility at various time scales.

Short-term IV, which responds more quickly to sudden shocks, can be given higher weights through dynamic adjustment of the decay factor λ, thereby enhancing model sensitivity.

Second, considering the asymmetric impact of political stability on volatility, policy uncertainty indices and macroeconomic expectations can be integrated as auxiliary variables. These variables can work synergistically with IV through EWMA's weighting mechanism to improve the capture of systemic risks.

Third, given the volatility characteristics vary significantly across markets, this specificity requires the model to adjust its scenario adaptability For high-volatility assets, such as the USD/ZAR exchange rate, a smaller λ can be used to accelerate the integration of IV information. For low-volatility assets, such as bond indices, λ can be increased appropriately to smooth short-term noise.

Finally, building on the RECH model's strengths in Value-at-Risk (VaR) forecasting, quantile regression can be added to the volatility output of EWMA-GARCH. This enhancement enables the model to not only predict overall volatility but also accurately characterize risks at extreme quantiles, thereby enhancing its applicability in risk management [9].

5. Conclusion

In summary, the core potential of EWMA-GARCH lies in integrating multi-source information with a concise framework. By continuously absorbing the stability of parametric models and the flexibility of non-parametric models, it is expected to become a universal volatility tool across markets and scenarios, providing more accurate technical support for option pricing and portfolio risk management.

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However, this paper still remains several limitations. Methodologically, the review mainly focuses on model formulations and theoretical aspects, lacking in-depth discussion on advanced estimation techniques or computational methods for handling large-scale, high-frequency data. Also, the literature coverage could be expanded to incorporate more recent studies on hybrid models or those integrating machine learning with GARCH frameworks.

In terms of content, while various models are discussed, empirical analyses with extensive real world financial data across different markets and asset classes are scarce, making it hard to fully assess model performance in diverse scenarios. To address it, future work could involve conducting comparative empirical studies using datasets from multiple financial markets and asset types. There should also be a deeper dive into novel computational approaches for efficient model estimation and prediction. Additionally, broadening the literature review to include the latest advancements in the field would enhance the review's comprehensiveness.

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