

Online ISSN

3007-3197

Print ISSN

3007-3189

<http://amresearchreview.com/index.php/Journal/about>

Financial Risk Modeling and Volatility Forecasting Using GARCH-Based Econometric Techniques

Shayan Mujahid *

Department of Management Sciences, Cecos University

shayanmujahid349@gmail.com

Syed Ghazanfer Inam

Mohammad Ali Jinnah University, Karachi

ghazanfer@jinnah.edu

Qurratulain Hanif

Biostatistician, Avicenna medical and dental college

anieebhatti9@gmail.com

Aroob Bin Habib

Department of Management Sciences, University of Wah

aroobhabib2002@gmail.com

Talha

University of Makran

talha@uomp.edu.pk

ABSTRACT

This paper examines the evolution, applications, and significance of Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models in financial risk modeling and volatility forecasting. Financial markets are characterized by volatility clustering, leptokurtosis, structural breaks, and asymmetric responses to market shocks, making traditional constant-variance models inadequate for modern risk analysis. The study discusses the theoretical foundations of ARCH and GARCH models and highlights the transition toward advanced asymmetric variants such as EGARCH, GJR-GARCH, TGARCH, and APARCH, which better capture leverage effects and non-linear volatility dynamics. Furthermore, the review evaluates estimation approaches including Maximum Likelihood Estimation (MLE), Quasi-Maximum Likelihood Estimation (QMLE), Bayesian inference, and heavy-tailed distribution assumptions for improving forecasting accuracy. Diagnostic testing procedures such as the Ljung–Box test, ARCH-LM test, and information criteria are also explored to assess model adequacy and predictive performance. Particular attention is given to the role of GARCH-based frameworks in calculating Value at Risk (VaR) and Expected Shortfall

(ES), which are essential tools for regulatory compliance and portfolio risk management under Basel III standards. The paper additionally investigates the integration of GARCH models with machine learning and deep learning techniques, including GRU and LSTM architectures, to enhance forecasting performance in high-frequency trading and cryptocurrency markets. Sector-specific applications in equity, foreign exchange, energy, and digital asset markets demonstrate the flexibility and robustness of GARCH methodologies. Overall, the review emphasizes that GARCH-based econometric techniques remain indispensable for understanding financial market uncertainty and for supporting data-driven investment and risk management decisions in increasingly volatile global markets.

Keywords— Financial risk modeling; Volatility forecasting; GARCH models; ARCH; EGARCH; APARCH; Value at Risk (VaR); Expected Shortfall (ES); Machine learning; Financial econometrics.

1. Introduction

The evolution of financial risk management is intrinsically linked to the ability of econometricians to model the latent nature of volatility. Unlike asset prices or returns, volatility is not directly observable in the market; it must be inferred through statistical abstractions that capture the underlying variance of return series (Engle, 2004). This imperative has led to a paradigm shift in financial economics, moving from static measures of risk to dynamic, conditional models that account for the time-varying nature of market uncertainty (IMF, 2018). The conceptual breakthrough achieved through the development of the ARCH (Autoregressive Conditional Heteroskedasticity) and GARCH (Generalized Autoregressive Conditional Heteroskedasticity) frameworks has provided the analytical foundation for everything from derivative pricing and asset allocation to the determination of regulatory capital under Basel III protocols (MDPI, 2026).

2. Theoretical Context and the Evolution of Conditional Heteroskedasticity

In the classical era of financial modeling, many assumptions were predicated on the notion of homoskedasticity the idea that the variance of the error term in a time series remains constant over time. However, empirical investigations of equity markets, foreign exchange, and commodity prices revealed significant deviations from this assumption. Financial time series frequently exhibit what are known as "stylized facts," including volatility clustering, leptokurtosis (fat-tailed distributions), and the leverage effect (Cont, 2001). Volatility clustering, a term popularized by Mandelbrot (1963), refers to the phenomenon where large changes in prices tend to be followed by large changes, and small changes by small changes. This implies that volatility persists in "bursts," creating distinct regimes of high and low risk (Bollerslev, 1986).

2.1 The ARCH Framework and the Genesis of Modern Risk Modeling

The formalization of time-varying volatility began with Robert Engle's seminal 1982 paper, which introduced the autoregressive conditional heteroskedasticity (ARCH) model (Mandelbrot, 1963). Engle recognized that while the unconditional variance of a series might be constant, the conditional variance—the variance given the information

Online ISSN

3007-3197

Print ISSN

3007-3189

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available at a specific point in time—could be modeled as a function of past squared innovations (Engle, 1982). For a return series r_t , let ϵ_t represent the unpredictable component or residual from a mean equation (such as an autoregressive moving average, ARMA, process), such that $\epsilon_t = \sigma_t z_t$, where z_t is an independent and identically distributed (i.i.d.) random variable with zero mean and unit variance (Tsay, 2013).

The ARCH (q) model specifies the conditional variance σ_t^2 as a linear combination of the q past squared residuals:

$$\sigma_t^2 = \omega + \sum_{i=1}^q \alpha_i \epsilon_{t-i}^2$$

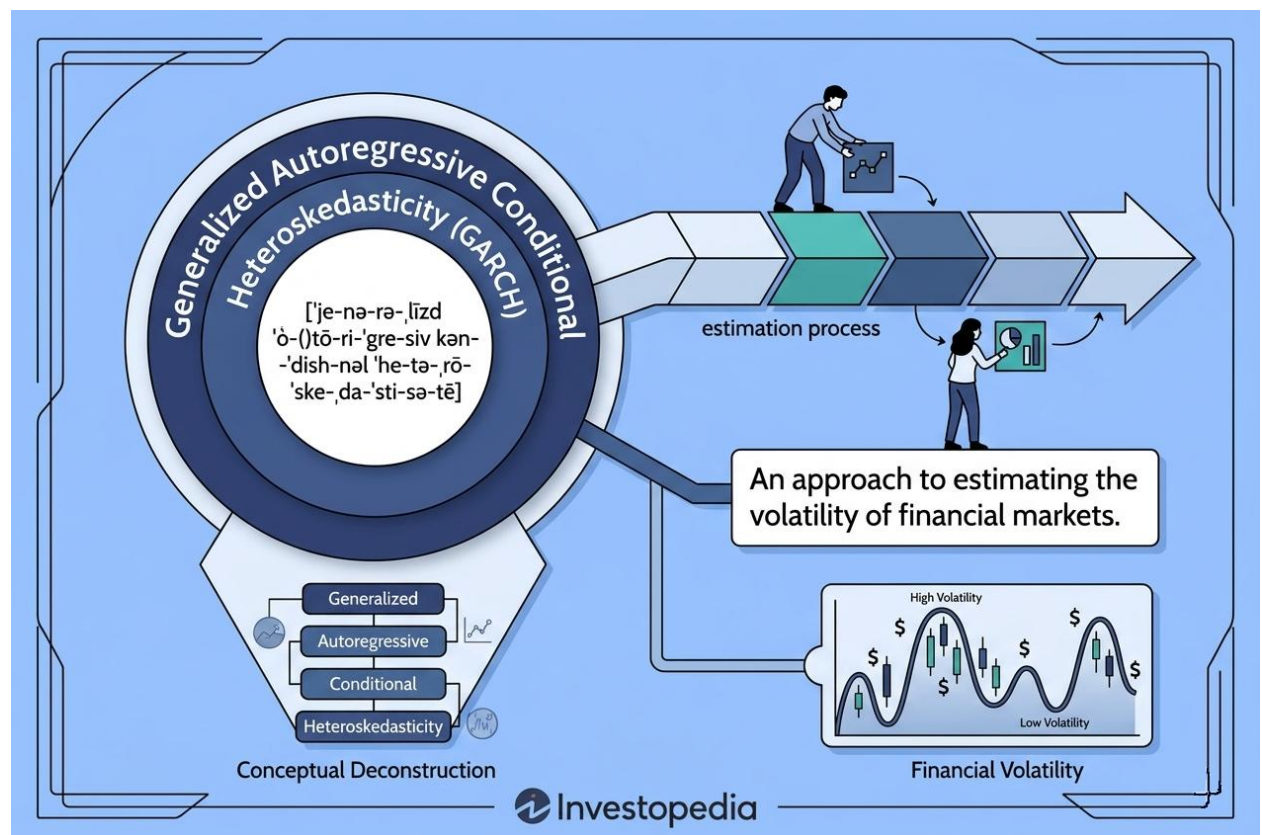
In this specification, $\omega > 0$ ensures a baseline level of volatility, while the α_i coefficients (where $\alpha_i \geq 0$) dictate the sensitivity of the current variance to recent shocks. Despite its revolutionary nature, the ARCH model suffered from several practical drawbacks. To capture the long-term persistence observed in many financial assets, the model often required a high number of lags (q), which complicated estimation and reduced degrees of freedom (Bollerslev, 1986). of freedom, and often led to violations of non-negativity constraints (Nelson, 1991).

2.2 The Transition to Generalized ARCH (GARCH)

To resolve the parameter inflation of the ARCH model, Tim Bollerslev introduced the generalized autoregressive conditional heteroskedasticity (GARCH) model in 1986 (Bollerslev, 1986). By incorporating an autoregressive component into the variance equation, Bollerslev allowed the current conditional variance to depend not only on past shocks but also on past values of the variance itself. This modification provided a more parsimonious way to capture long-memory effects in volatility, functioning essentially as an ARMA process for the squared residuals (Taylor, 1986). The standard GARCH (p, q) specification is:

$$\sigma_t^2 = \omega + \sum_{i=1}^q \alpha_i \epsilon_{t-i}^2 + \sum_{j=1}^p \beta_j \sigma_{t-j}^2$$

Figure: 1 The Transition to Generalized ARCH (GARCH) (or 4. Estimation Techniques and Distributional Assumptions)



The GARCH (1,1) model has become the ubiquitous "workhorse" of applied finance because it can capture the volatility dynamics of most assets with just three parameters. The sum $\alpha + \beta$ serves as a critical measure of volatility persistence. When this sum is close to unity, shocks to the system decay at an extremely slow rate, implying that a period of high volatility today will exert a significant influence on the risk profile of the asset for the foreseeable future (Alexander, 2008). In cases where $\alpha + \beta = 1$, the process becomes an integrated GARCH (IGARCH), where the unconditional variance is undefined and shocks have a permanent effect on the variance trajectory (Engle & Bollerslev, 1986).

Table 1: Key Characteristics of Basic GARCH Models

Model Type	Key Characteristic	Mathematical Innovation	Primary Use Case
ARCH	Conditional heteroskedasticity	Variance as a function of past squared shocks	Short-term volatility bursts
GARCH	Volatility persistence	Inclusion of lagged conditional variance terms	Long-term risk management

IGARCH	Persistent shocks	Parameter sum equals 1; unit root in variance	Modeling permanent risk shifts
GARCH-M	Risk-return tradeoff	Conditional variance enters the mean equation	Asset pricing and risk premium

3. Asymmetric Dynamics and the Leverage Effect

One of the most critical observations in equity market dynamics is that negative returns (bad news) typically generate a larger increase in volatility than positive returns (good news) of an equivalent magnitude. This "leverage effect" is theorized to stem from both financial mechanics as a firm's stock price falls, its debt-to-equity ratio rises, making it riskier and behavioral factors, such as "fear" spreading more rapidly than "greed". Standard GARCH models are symmetric and cannot account for this bias, necessitating the development of asymmetric variants (Hansen & Lunde, 2005).

3.1 Exponential GARCH (EGARCH) and Log-Variance Modeling

Proposed by Nelson (1991) in his seminal work, the exponential GARCH (EGARCH) model addresses two primary limitations of symmetric GARCH: the inability to model asymmetry and the need for restrictive non-negativity constraints on parameters. By modeling the natural logarithm of the conditional variance, EGARCH ensures that σ_t^2 is strictly positive for any real-valued parameters (Nelson, 1991). The EGARCH (1,1) model is formulated as:

$$\ln(\sigma_t^2) = \omega + \beta \ln(\sigma_{t-1}^2) + \alpha \left(\frac{|\epsilon_{t-1}|}{\sigma_{t-1}} - \mathbb{E}[|z_{t-1}|] \right) + \gamma \frac{\epsilon_{t-1}}{\sigma_{t-1}}$$

The coefficient γ captures the asymmetry of the response (McAleer & Hafner, 2014). A negative γ indicates that negative shocks increase the log-variance more than positive ones, a common finding in equity markets (Nelson, 1991; Bekaert & Wu, 1997). Conversely, in certain commodity or energy markets, an "inverse leverage effect" may be observed where price spikes (positive shocks) create more turbulence than price drops (Chen & Mu, 2021; Baur & Dimpfl, 2018).

3.2 The GJR-GARCH and Threshold GARCH (TGARCH) Models

The GJR-GARCH model, introduced by Glosten, Jagannathan, and Runkle (1993), provides an alternative, piecewise-linear approach to capturing asymmetry. It incorporates an indicator function that "switches on" specifically for negative residuals (Kyriakopoulou, 2015). The variance equation is:

$$\sigma_t^2 = \omega + \alpha \epsilon_{t-1}^2 + \gamma I_{t-1} \epsilon_{t-1}^2 + \beta \sigma_{t-1}^2$$

where $I_{t-1} = 1$ if $\epsilon_{t-1} < 0$, and 0 otherwise. In this framework, the impact of a positive shock is α , whereas the impact of a negative shock is $\alpha + \gamma$. The model is nested such that if $\gamma = 0$, it collapses back to a standard GARCH (1,1). The threshold GARCH (TGARCH) proposed by Zakoïan is nearly identical but focuses on the conditional standard deviation rather than the variance, which can sometimes provide more stable estimates in datasets with extreme outliers (Zaffaroni, 2009).

3.3 Asymmetric Power ARCH (APARCH) and Model Generalization

The APARCH model by Ding et al. (1993) is a highly flexible extension that generalizes the GARCH structure by allowing the power to which the standard deviation is raised (δ) to be estimated as a parameter, rather than being fixed at 2 (Bollerslev, 1986). This allows the model to capture a broader range of tail behaviors and persistence patterns. The APARCH model nests many other specifications, including GARCH and GJR-GARCH, making it a powerful tool for academic model selection. Research into high-frequency Nordic indices and cryptocurrency pairs has often found APARCH to be superior in predicting realized volatility due to its ability to adapt to the varying leptokurtosis of different assets (Engle, 1982).

Table 2: Features of Asymmetric GARCH Models

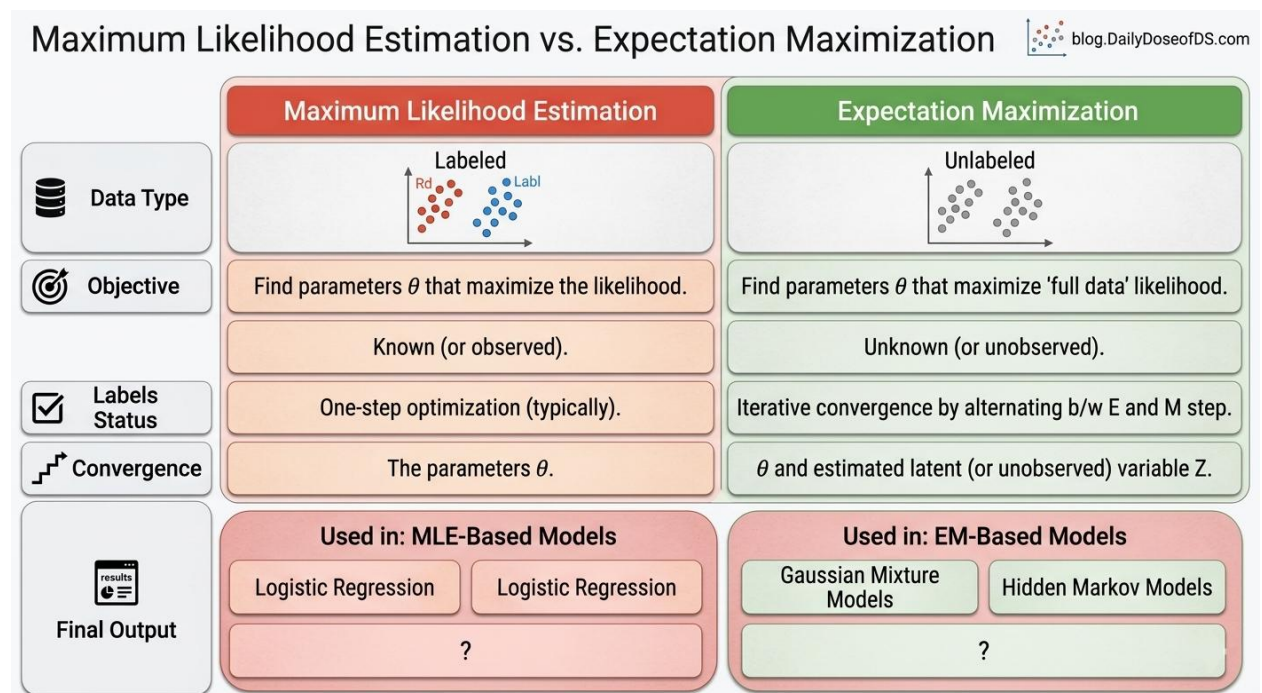
Asymmetric Model	Mechanism for Asymmetry	Non-negativity Strategy	Advantage
EGARCH	$\gamma \left(\frac{\epsilon_t}{\sigma_t} \right)$ term in log-variance	Logarithmic transformation	No sign restrictions on parameters
GJR-GARCH	Indicator function $I_{t-1}(\epsilon_{t-1} < 0)$ for negative shocks	Explicit parameter constraints	Ease of interpretation; nested in standard GARCH
APARCH	Power parameter δ and asymmetry term γ shift	Parameter constraints	Highly flexible; nests multiple models
TGARCH	Thresholding on conditional standard deviation	Explicit parameter constraints	Robustness to extreme volatility shocks

4. Estimation Techniques and Distributional Assumptions

The accuracy of GARCH forecasting is deeply contingent upon the statistical method used to estimate parameters and the choice of the error term's distribution. While early applications relied heavily on the Gaussian (Normal) distribution, the presence of "fat tails" in empirical finance often leads to a systematic underestimation of risk when using normal-based models (Engle, 2001).

Maximum Likelihood Estimation (MLE) seeks to find parameter values that maximize the joint probability density of the observed data. In GARCH modeling, this requires the specification of a density for the standardized residuals. When the data is non-normal, researchers often turn to the student's t-distribution or the Generalized Error Distribution (GED) to provide a better fit for the extremes (Bollerslev & Wooldridge, 1992).

Figure:2 Comparative Overview of Maximum Likelihood Estimation vs. Expectation Maximization



Quasi-Maximum Likelihood Estimation (QMLE) is a robust alternative that remains consistent even if the assumed distribution (typically Gaussian) is incorrect. However, while the parameter estimates remain consistent under QMLE, the standard errors will be biased unless a "sandwich" covariance estimator is used to provide robust inference (White, 1982). This is particularly important in high-frequency trading (HFT) environments where microstructure noise and frequent "jumps" make the normality assumption untenable (Aït-Sahalia & Jacod, 2009).

4.2 Bayesian Estimation and Heavy-Tailed Innovations

A more recent development in the literature is the application of Bayesian estimation techniques to GARCH models. By using informative priors such as truncated normal priors on the persistence parameters (α , β) to ensure stationarity Bayesian methods can produce more realistic posterior distributions for parameters than frequentist MLE (Yao, 2025). Studies applying Bayesian GARCH (1,1) with Student-t innovations to the VIX index (the Cboe Volatility Index) have demonstrated that these models can effectively capture "investor fear" and uncertainty more accurately than standard asymmetric models, especially during periods of global macro shocks (Virbickaite et al., 2025).

4.3 Innovations in Fast Estimation: The NCT-APARCH Model

In practical risk management settings, such as bank-wide portfolio monitoring, the computational cost of re-estimating GARCH models for thousands of assets daily can be prohibitive. To address this, the non-central t (NCT) GARCH approach has been

developed (Bandyopadhyay, 2016). By using a lookup table (FastNCT) and saddlepoint approximations (SPA) for the density, researchers can estimate complex APARCH models in a fraction of the time required by standard iterative optimization. This method has proven particularly effective for calculating Expected Shortfall for the DJIA 30 stocks, outperforming standard GARCH-t models in both speed and out-of-sample quantile accuracy (Mahmud et al., 2025).

5. Diagnostic Testing and Model Selection

Once a GARCH model has been estimated, a rigorous battery of diagnostic tests is required to ensure that the conditional variance has been correctly specified and that no heteroskedasticity remains in the residuals (Osho & Oloyede, 2024).

5.1 Residual Autocorrelation and ARCH Effects

The primary diagnostic tool is the analysis of the standardized residuals $\hat{z}_t = \hat{\epsilon}_t / \hat{\sigma}_t$. If the model is well-specified, these residuals should be independent and identically distributed (i.i.d.) random noise. Recent empirical research on financial markets continues to utilize these diagnostics to trace the temporal dynamics of risk (MDPI, 2026).

Ljung–Box Q-test: This test is applied to both the standardized residuals (to check for mean misspecification) and the squared standardized residuals (to check for remaining variance dynamics). A rejection of the null hypothesis in the squared residuals indicates that the GARCH model has failed to fully capture the volatility clustering, a common issue identified in recent studies of heavy-tailed innovations (Han, 2021).

ARCH-LM test: Developed by Engle, this Lagrange multiplier test specifically looks for remaining ARCH effects. Modern applications often use this test to validate whether high-frequency volatility measures have been adequately "de-volatilized" (Boswijk et al., 2024).

Li–Mak test: In cases where asymmetric distributions are used for the errors, the Li–Mak test has been found to have higher empirical power than the Ljung–Box test, making it a superior choice for validating EGARCH and GJR-GARCH models. Recent comparative analyses emphasize that while EGARCH-t models are better at capturing historical volatility mechanisms and leverage effects, they require these rigorous diagnostic tests to ensure predictive utility (Zeus Press, 2026).

5.2 Information Criteria and Model Comparison

Because GARCH models are often used for forecasting, the principle of parsimony is paramount. The Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) are used to rank competing models. BIC generally imposes a heavier penalty on the number of parameters, making it more conservative in model selection. In practice, a GARCH (1,1) is often preferred over higher-order models ($p, q > 2$) unless statistical tests suggest substantial improvements in fit (Wang et al., 2022).

Table 3: Common Diagnostic Tests for GARCH Specifications

Diagnostic Test	Focus Area	Null Hypothesis (H0)	Implication of Rejection
Ljung-Box (Squared)	Variance dynamics	No serial correlation in squared residuals	Remaining ARCH effects; increase lags
ARCH-LM	ARCH effects	No ARCH components in	Misspecified variance

		residuals	equation
Jarque-Bera	Normality	Residuals are normally distributed	Need for Student-t or Skewed-t errors
Li-Mak	Asymmetry	No remaining asymmetric heteroskedasticity	Need for a different asymmetric GARCH
Diebold-Mariano	Forecast comparison	Two forecasts have equal accuracy	One model is significantly superior

6. Structural Breaks and Regime Shifts

A major challenge in long-term volatility forecasting is the assumption of parameter stability. Markets are subject to structural breaks sudden changes in the baseline level or persistence of volatility caused by events such as the 2008 financial crisis, the COVID-19 pandemic, or significant policy changes (Bulut, 2024).

6.1 The ICSS Algorithm and Parameter Overestimation

Ignoring structural breaks often leads to an upward bias in the estimated persistence ($\alpha + \beta$), a phenomenon where the model "confuses" a shift in the mean level of variance with high persistence. The Iterated Cumulative Sum of Squares (ICSS) algorithm is frequently used to detect these break points (Inclán & Tiao, 1994). By identifying specific dates where the variance regime changed, researchers can implement regime segmentation estimating the GARCH model only on data within the current regime (Stărică & Granger, 2005). Studies on Latin American indices (IGBVL, IPSA) have shown that accounting for these breaks improves forecast accuracy in the short term, although this advantage can dissipate if the break is very recent, leading to a limited sample size for estimation (Babikir et al., 2012).

7. Risk Management Metrics: VaR and Expected Shortfall

The ultimate utility of GARCH models lies in their ability to generate accurate forecasts for risk metrics used in regulatory compliance and internal capital allocation (Ataurima Arellano & Rodríguez, 2025).

7.1 Value at Risk (VaR) and Backtesting

Value at risk (VaR) represents the maximum loss expected over a certain horizon at a given confidence level. A GARCH-based VaR forecast is calculated as:

$$\text{VaR}_{t+1}^p = \hat{\mu}_{t+1} + \hat{\sigma}_{t+1} F^{-1}(p)$$

where $F^{-1}(p)$ is the quantile of the assumed error distribution. The accuracy of these forecasts is evaluated using backtesting procedures, such as the Kupiec (POF) test and the Christoffersen interval forecast test, which check whether the number of "violations" (actual losses exceeding VaR) matches the expected probability p (Mikosch & Stărică, 2004).

7.2 Expected Shortfall (ES) and Tail Risk

While VaR is intuitive, it lacks "coherence" because it does not account for the magnitude of losses beyond the threshold. Basel III has therefore recommended a shift toward Expected Shortfall (ES), which averages the losses in the tail. Calculating ES for GARCH models with non-normal innovations is mathematically intensive (Lamoureux & Lastrapes, 1990). For a Student's t-distribution, the ES formula for k -period returns involves integrating the predictive density over the tail region, a process

that can be expedited through Filtered Historical Simulation (FHS). FHS combines GARCH filtering which removes the volatility clustering with a non-parametric bootstrap of the residuals, providing a robust way to capture tail risk without imposing a strict distributional form (Malik, 2011).

8. High-Frequency Trading and Machine Learning Hybrids

The modern trading landscape, characterized by high-frequency execution and algorithmic strategies, has pushed GARCH models toward integration with machine learning (ML) and deep learning architectures (Hillebrand, 2005).

8.1 The Rise of GARCH-RNN Hybrids

Traditional GARCH models are linear in their variance specification, which may limit their ability to capture highly complex, non-linear dependencies in financial time series. To overcome this, researchers have developed integrated frameworks like the GARCH-GRU (Gated Recurrent Unit) and GARCH-LSTM (Long Short-Term Memory) models. In these structures, the GARCH formulation is embedded directly into the neural network's recurrent cell, allowing the model to jointly learn "stylized facts" through the econometric component and temporal patterns through the deep learning component (Diebold, 1986). Empirical evaluations on S&P 500 and cryptocurrency data indicate that GARCH-GRU models achieve lower Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) than standalone models, while also being more computationally efficient than LSTM counterparts (Tsay, 2013).

8.2 Ensemble Learning and Real-Time Adjustment

In HFT environments, GARCH models are often used as part of an ensemble. For instance, a model may use GARCH and EGARCH outputs as features for a Gradient Boosting (XGBoost) or Random Forest model. This hybrid approach has been shown to reduce forecast error by approximately 12% in HFT markets, where the ML component can learn to "correct" GARCH residuals for microstructure noise and liquidity-driven volatility spikes (Zaffaroni, 2009). Furthermore, real-time parameter calibration strategies allow these models to adjust to "circuit changes" and "power shifts" in the market within milliseconds (Hansen & Lunde, 2005).

9. Forecast Evaluation and the Choice of Loss Functions

A fundamental problem in volatility research is the lack of a ground-truth "observed" volatility against which to test forecasts. Patton (2011) and Hansen and Lunde (2005) have addressed this by developing robust loss functions that maintain the consistent ranking of models even when using noisy proxies like squared returns or realized volatility (RV) (Kyriakopoulou, 2015).

9.1 MSE vs. Q-LIKE Loss Functions

The two most common robust loss functions are Mean Squared Error (MSE) and Quasi-Likelihood (Q-LIKE).

- **MSE:** This symmetric loss function measures the squared difference between the forecast and the proxy. However, MSE is highly sensitive to outliers a single extreme price jump can disproportionately penalize a model that was otherwise accurate (Bulut, 2024).
- **Q-LIKE:** This function is based on the standardized forecast error and is less sensitive to the absolute level of volatility. Patton and Sheppard (2009) have shown that Q-LIKE yields the greatest statistical power in identifying the

optimal volatility model. In many empirical studies, while MSE may suggest that a standard GARCH(1,1) is sufficient, Q-LIKE often reveals that an asymmetric model like APARCH or GJR-GARCH is significantly superior (Mahmud et al., 2025).

Table 4: Evaluation of Robust Volatility Loss Functions

Loss Function	Mathematical Form (Simplified)	Robustness Property	Interpretation Sensitivity
MSE	$\sum(\sigma^2 - RV)^2$	Robust to noise in proxy	Sensitive to extreme outliers / volatility spikes
Q-LIKE	$\sum \left(\frac{RV}{\sigma^2} - \ln \left(\frac{RV}{\sigma^2} \right) - 1 \right)$	Robust; consistent ranking	Focuses on standardized percentage errors
MAE	$\sum \sigma^2 - RV $		
HR Loss	Flexible homogeneous robust form	Robust; shape-adjustable	Can be tuned for under-prediction penalty

10. Sector-Specific Volatility Dynamics

The efficacy of different GARCH variants depends heavily on the asset class and the specific economic conditions of the trading environment (Hansen & Lunde, 2005).

10.1 Foreign Exchange (FX) Markets

In the FX market, volatility is often influenced by global macro shocks and the relative interest rate policies of central banks. A study of major pairs (EUR/USD, USD/JPY, GBP/USD) found that EGARCH models provide the best fit, as they capture the significant impact of "news" shocks better than symmetric GARCH. Interestingly, the USD/JPY pair often exhibits lower annualized volatility and higher stability during global crises compared to other majors, making it a key component for low-risk portfolio allocation (Aït-Sahalia & Jacod, 2009).

10.2 Energy and Commodity Markets

Energy markets (natural gas, electricity) are characterized by extreme price spikes and seasonal patterns. In these markets, the EGARCH model is highly valued for its ability to model log-variance, which prevents large shocks from "blowing up" the variance estimate directly a common issue with linear GARCH models. Furthermore, these markets often exhibit inverse leverage effects, where rapid price increases trigger more "panic" and volatility than price declines (Virbickaite et al., 2025).

10.3 Cryptocurrency Markets

Cryptocurrency volatility modeling is arguably the most challenging area of modern econometrics. Assets like Bitcoin and Dogecoin are characterized by extreme sentiment-driven volatility and a lack of fundamental anchors. Research benchmarking 10 major coins from 2020-2025 shows that traditional GARCH models work well for "stable" coins like Bitcoin and Ethereum where volatility clustering is persistent (Osho & Oloyede, 2024). However, for "meme" coins like Shiba Inu, deep learning models (GRU, TDNN) significantly outperform GARCH by capturing non-linear, non-stationary patterns. Hybrid GJR-GARCH models have also shown promise in this

Online ISSN

3007-3197

Print ISSN

3007-3189

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sector by directly modeling the intense asymmetric shocks typical of crypto "flash crashes" (Aït-Sahalia & Jacod, 2009).

11. Conclusion

GARCH-based econometric techniques have transformed modern financial risk modeling by providing dynamic frameworks capable of capturing time-varying volatility and complex market behavior. From the foundational ARCH and GARCH models to advanced asymmetric specifications such as EGARCH, GJR-GARCH, TGARCH, and APARCH, these methodologies have significantly improved the accuracy of volatility forecasting and risk assessment. Their ability to model volatility clustering, leverage effects, heavy tails, and structural breaks makes them highly effective for applications in stock, foreign exchange, commodity, and cryptocurrency markets. The review further demonstrates that reliable parameter estimation methods, robust diagnostic testing, and appropriate distributional assumptions are essential for improving predictive performance and minimizing forecasting errors. In addition, the integration of GARCH frameworks with machine learning and deep learning models has opened new opportunities for real-time forecasting and high-frequency financial analysis. Hybrid approaches combining econometric rigor with artificial intelligence provide enhanced adaptability to non-linear and rapidly changing market environments. Overall, GARCH-based models remain fundamental tools for portfolio optimization, derivative pricing, Value at Risk estimation, and regulatory risk management. Despite the emergence of advanced computational methods, GARCH frameworks continue to offer strong interpretability, flexibility, and practical relevance. Future research should focus on hybrid forecasting systems, structural break adaptation, and the incorporation of big data analytics to further improve the robustness and efficiency of financial volatility modeling in global financial markets.

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Online ISSN

3007-3197

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3007-3189

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