Conclusion: Methodological Synergy and Divergence

In this study, we employed two distinct paradigms: **deep learning** and **classical econometrics**, to model and forecast financial time series. The **LSTM network** leveraged its ability to learn nonlinear temporal dependencies directly from raw data, utilizing sequences of historical features (e.g., prices, volume, and volatility) to predict future volatility. Its architecture, designed to retain long-term memory through recurrent layers and dropout regularization, allowed it to adaptively capture complex patterns in market behavior.

Conversely, the **ARMA-GARCH framework** adopted a modular approach: the ARMA component modeled linear dependencies in the mean equation, while the GARCH extension explicitly parameterized time-varying volatility through lagged residuals and conditional variances. This method's strength lies in its interpretability, statistical rigor, and adherence to stylized facts of financial markets (e.g., volatility clustering).

While the LSTM's flexibility accommodates unstructured, high-dimensional inputs, the ARMA-GARCH pipeline operates under well-defined assumptions (e.g., stationarity) and offers transparent parameter estimates. The former excels in learning latent patterns without prior constraints, whereas the latter provides a parsimonious representation of market dynamics grounded in economic theory. Together, these approaches underscore the complementary roles of data-driven machine learning and theory-guided econometrics in financial forecasting, each addressing the challenges of uncertainty and nonlinearity through its unique lens.