Peer Review of "How well can time-series models predict short-term volatility in the NOK/EUR exchange?"

Brief summary of contents

This report investigates how well different time-series models can predict short-term changes in the volatility of the NOK/EUR exchange rate. The group began by collecting historical exchange rate data from Yahoo Finance and transforming it into log returns to ensure stationarity. The dataset they use spans from January 1, 2015, to January 1, 2025. Several statistical tests are conducted, including the Augmented Dickey-Fuller (ADF) test, Ljung-Box test, and ARCH test, to evaluate stationarity, autocorrelation and time-varying variance.

The group applied four models, ARIMA, GARCH, FIGARCH, and TARCH. Each model was evaluated and compared using AIC and BIC, which measure how well the model fits the data, and RMSE and MAE, which measure prediction error. Then, they used the GARCH model to forecast volatility over a 30-day period and compared this with the actual volatility using a rolling window approach.

The report concludes that GARCH models work well for capturing general patterns in volatility but struggle to predict unexpected jumps, such as the sudden spike on December 31, 2024.

Strengths of report:

- **Clear structure and flow:** The report is well-organized, beginning with a clear problem statement, followed by data processing, modeling, evaluation, and a conclusion. This makes the analysis easy to follow and to understand for the reader.
- **Relevant and timely research question:** The topic of exchange rate volatility is both timely and practically important, especially in a Norwegian context. The focus on short-term volatility is also appropriate for the methods used.
- **Use of several models:** The group compares several different time-series models (ARIMA, GARCH, FIGARCH, TARCH). This strengthens the empirical findings and provides a broader perspective on model performance.
- **Use of statistical tests:** The report applies relevant econometric tests, such as ADF, Ljung-Box, and ARCH tests, showing that they understand both how and why these tests are used in time-series.
- **Explanation of AIC and BIC:** It was positive that the report not only mentioned the use of AIC and BIC but also explained their purpose. By clarifying that these criteria help balance model fit with simplicity, the report shows a good understanding of the trade-off between predictive accuracy and model complexity.
- **Critical reflection on model limitations**: The limitations of each model and where the models fall short, are discussed openly. For example, the report explains how GARCH cannot handle sudden shocks in the market.
- **Helpful visualizations**: The plots make the analysis easier to follow, especially the comparison between predicted and actual volatility.

- **Responsible use of LLMs**: The group clearly states that LLMs were used for debugging and understanding code, not for solving the core problem. This shows transparency and good academic practice.

Suggestions for improvement

- **Clarify the choice of forecast horizon and window length:** The report uses a 30-day forecast horizon and a 30-day rolling window to calculate realized volatility, but it does not explain why this time frame was chosen.
- **Clarify the trade-off in model results:** The report makes a good attempt at explaining the difference between prediction errors (RMSE/MAE) and model fit (AIC/BIC). They note that ARIMA has lower prediction errors, while TARCH has better fit according to information criteria. However, the explanation could be made even clearer by discussing when it makes sense to prioritize prediction accuracy over model simplicity or fit, especially in the context of volatility forecasting. This would help the reader better understand the practical implications of the results.
- **More discussion on model choice:** The report could be improved by adding a short explanation of why these models (ARIMA, GARCH, FIGARCH, TARCH) were chosen. This would help the reader understand why these models are useful for analyzing financial time series and changes in volatility.
- **Clarify why stationarity is important:** A short explanation of why stationarity is needed in time-series modeling would help the reader better understand the overall context and purpose of the transformations.
- **Include a practical context for volatility:** Adding a short explanation of why volatility matters in real-world situations, for example, for investors, or central banks, would strengthen the report. Additionally, it may be useful to mention how volatility has historically been linked to real events, such as financial crises, interest rate changes, or political uncertainty. This would help the reader understand both how the models work and why volatility forecasting is important.