Forecasting oil price realized volatility

Project: International transmission and predictability of asset price volatility

Author
SERVOS DIMITRIOS, 1067563

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1 Forecasting methodology and evaluation

The emphasis on model evaluation has been given to out-of-sample performance. To achieve this, we have set aside some of our known data (ex-post) to use as an estimation period, allowing us to evaluate our model. Our sample consists of 120 monthly observations spanning a period of 10 years from May 2014 to April 2024. The sample was divided into 100 observations corresponding to the in-sample period, which accounts for approximately 80% of the total sample, and the remaining 20 observations correspond to the out-of-sample period. Next, we estimated an AR(1) model for the price realized volatility of Oil (WTI), following Andersen and Bollerslev (1998), which serves as the naive model, meaning a model that has undergone minimal effort to be used for prediction and comparison with other models. In our case, we compared it with an AR(1)-X type model, where X corresponds to the lag realized volatility of the S&P 500. We selected a rolling window (static) and direct forecasting strategy to generate out-of-sample forecasts for up to 3 months ahead. This means that after each estimation, we remove the first observation, making the next one available. This keeps the number of observations we use constant, ensuring that our forecasts are comparable (rolling window-fixed window length). Finally, to move to the next forecast, we re-estimate the parameters(direct forecasts). Thus, we have 20 1-step ahead forecasts, 19 2-step ahead forecasts, and 18 3-step ahead forecasts.

As a method of evaluating the accuracy of the predictions from the two models, we will use the statistical loss function Mean Absolute Error (MAE):

$$MAE = \frac{1}{n} \cdot \sum_{i=1}^{n} |y_i - \hat{y}_i|$$

Where n depends on the forecast horizon and is the number of forecasts, y_i corresponds to the actual values of the dependent variable, and $\hat{y}_i$ corresponds to the predicted values of the dependent variable from the regression model.

2 Results

Table 1: Out-of-sample results.

Benchmarks	1-step	2-step	3-step
AR(1)	54.90	61.70	63.21
AR(1)-X	158.76	141.11	151.72

Note: Smaller values better forecasting ability.

We will evaluate the predictive accuracy of our models from 1 to 3 days ahead, using the Mean Absolute Error (MAE) as the evaluation metric. The results for the MAE are presented in Table 1, where the first column indicates the MAE values for the AR(1) model, and the second column corresponds to the AR(1)-X model. We can observe that the AR(1) model outperforms the AR(1)-X model in terms of predictive performance regardless of the forecast horizon, as its MAE is lower. This means that, on average, the predictions of the AR(1) model are closer to the actual values. Regarding the AR(1) model, as the forecast horizon increases, the predictive accuracy of the model decreases, unlike the AR(1)-X model, where it improves at the 2 steps-ahead forecast and then increases again, with the worst performance at the 1 step-ahead forecast. The volatility of the S&P 500 in the AR(1)-X model failed to provide any predictive information compared to the simpler model, with 2 to 3 times larger errors. This indicates that, regarding the volatility of oil, the simpler model yields much better predictive results.