INTERNATIONAL TRANSMISSION AND PREDICTABILITY OF ASSET PRICE VOLATILITY

Part B: forecasting

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In this part of the assignment, we have divided our data into two periods: a training period consisting of the first 100 observations, and an out-of-sample forecasting period consisting of the remaining 20 observations. We applied a first log difference transformation to our monthly annualized oil price volatility chnage and the natural gas price monthly annualized volatility change data before estimating the models. We first estimated an Autoregressive (AR(1)) model for our transformed oil price volatility, using a rolling window approach with a fixed window length. This AR model served as our naïve model for comparison. Next, we extended our analysis to an Autoregressive with Exogenous Variables (AR-X(1)) model, where the second asset volatility served as an additional predictor. Specifically, we used the first log differences of the monthly natural gas price's annualized volatility change an independent variable to forecast the first log differences of oil price volatility change. We also computed a no-change model (NC), where we simply used the last observed value as the forecast for each period. To evaluate the performance of these models, as a statistical loss functions we chose the Mean Absolute Error (MAE) of our models, for each step-ahead forecast (1-, 2-, and 3-steps ahead). By comparing the results of these models, we aim to assess their effectiveness in forecasting oil price volatility and determine which approach yields the most accurate predictions.

The following table 1 displays the MAE for for each of the three models across 1-step, 2-step, and 3-step ahead predictions.

Model	**1-Step Ahead**	**2-Step Ahead**	**3-Step Ahead**
AR(1)	0.016173	0.017913	0.017136
AR(1)-X	0.016191	0.017931	0.016997
NC	0.018971	0.019146	0.018608

Table 1: Mean Absolute Error (MAE) for 1-step, 2-step, and 3-step ahead predictions by each model.

Looking at the results we first notice that except for the NC model, which demonstrates its lowest Mean Absolute Error (MAE) at the 3-step ahead prediction horizon, both the AR(1) and AR(1)-X models showcase their most accurate fit to the out-of-sample data at the 1-step ahead prediction, as anticipated. Additionally, it's noteworthy that the AR(1) model exhibits the lowest Mean Absolute Error (MAE) across all prediction horizons, with the exception of the 3-step ahead horizon where it is seemingly outperformed by the AR(1)-X model. The overall minimum MAE is observed for the AR(1) model at the 1-step ahead horizon, this observation leads us to asses the AR(1) model, at the 1-step ahead horizon, as the most efficient/effective predictive model among the considered alternatives.

Yet t is crucial to highlight that all models demonstrate relatively small MAEs, with particularly close performance observed between the AR(1) and AR(1)-X models. To further illustrate this point we include a graphical representation 1 depicting the predictions of all three models predictions(at the 1-step ahead horizon) against actual out-of-sample data for a forecasting horizon of 20 months. This graphical comparison offers a visual confirmation of the models' performance alignment and reinforces the overall effectiveness of the predictive approaches employed.

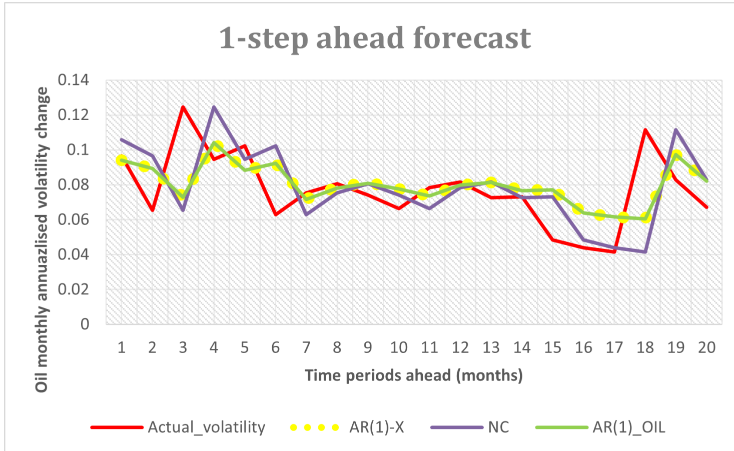

Figure 1: monthly annualized volatilities change predictions/ actual volatility change, plotted against forecasting horizon (20 months), created using excel.

Concluding, our analysis reveals the efficacy of employing Autoregressive (AR) models in forecasting oil price volatility change. By dividing our data into distinct training and out-of-sample periods and employing log difference transformations, we were able to construct models that provide accurate predictions. Specifically, the AR(1) model emerged as the most efficient in capturing the dynamics of oil price volatility, particularly at the 1-step ahead prediction horizon. Despite the slight deviation observed at the 3-step ahead horizon, where the AR(1)-X model demonstrated a marginally lower Mean Absolute Error (MAE), the AR(1) model maintained its overall superiority. Importantly, all models demonstrated relatively small MAEs, highlighting their effectiveness in forecasting. Moreover, the close alignment in performance between the AR(1) and AR(1)-X models underscores the robustness of our forecasting approach.