FORECASTING OIL PRICE VOLATILITY: THE ROLE OF MIXED-FREQUENCY-DATA (MIDAS) MODEL

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Overview

The increase in crude oil price volatility observed particularly around the period of the global financial crisis has created new interest into how to improve volatility forecasts. It is of primary importance for energy researchers, firms, financial market participants and policy makers to have models available that can provide accurate forecasts of oil price volatility.

Furthermore, in the literature, high oil price volatility periods have also caused new debate on the potential drivers (Kilian and Murphy, 2014; Van Robays, I., 2016; Degiannakis and Filis, 2017). Comprehending oil price volatility determinants is also crucial due to the fact that oil price volatility by itself could have a negative impact on economic activity (Jo, 2014; Van Robays, I., 2016). At the same time, the literature has experienced increased emphasis on the link between oil and financial markets. The critical question for this new link is whether financial market information can assist in forecasting oil price volatility. Therefore, this paper focuses not only on forecasting oil price volatility but also its potential determinants in the context of when they are most likely to exert their predictive power. The study of Degiannakis and Filis (2017) is the first study to extract information from other markets to help improve oil price volatility forecasts. However, their study forecasts daily oil price volatility whereas this paper forecasts on a monthly basis. The rationale for this is that policy makers, firms and oil companies are more interested in the longer run forecasts and a wider range of oil benchmarks and, in consequence, this paper uses both Brent and WTI volatility.

In more detail, this study investigates whether higher frequency (weekly) financial indices (both their volatilities and returns) help to improve the lower frequency (monthly) crude oil price realized volatility, using the MIDAS model. In this way, we assess whether there is useful predictive information for monthly oil price volatility in higher frequency data from financial markets. Using MIDAS models, we examine a large group of financial and economic variables which include either the returns and the volatilities of other asset class indices such as the Baltic Dry Index (proxy for global macroeconomic conditions), the Commodity Future Price Index (proxy for commodities market conditions), the MSCI World Index, the MSCI World Energy Index, S&P GSCI Index, S&P GSCI Energy Index (as proxies for global financial conditions), and Trade-weighted US exchange rate (proxy for global foreign exchange market).The use of these asset classes is motivated by Degiannakis and Filis (2017) who show that daily oil price volatility forecasts are improved when the information of asset volatilities that belong to these asset classes is incorporated to the forecasting models. Our data period is from January 3, 1995, to March 31, 2017. Thus, to forecast monthly oil price volatility, our initial sample size is 119 months and the last 148 months are used to evaluate the out-of-sample volatility forecasts. Since 2005/2006 onwards oil prices started to reach much higher price levels which would change the behaviour of volatility. Thus we ensure our out-of-sample covers this more turbulent period.

Methods

As the forecast strategy we follow ;

Step 1: Estimate the naïve and benchmark models (random-walk, AR(1), AR(12), AR(24) and HAR).

Step 2: Estimate MIDAS-HAR using one exogenous asset class variable at a time.

(separately the log-returns and realized volatility series)

These models are denoted as MIDAS-HAR-RV and MIDAS-HAR-RET.

In order to assess the predictive information of the high frequency data on the monthly oil price volatility, we employ the MIDAS model with the polynomial distributed lag weighting that was first proposed by Almon (1965). This is expressed as follows:

$$y_t = X'_{t-i}\beta + \sum_{j=0}^{k-1} X'^{(W)}_{(t-\tau-is)/s} \left(\sum_{j=0}^{p} \tau^j \theta_j\right) + \varepsilon_t,$$

where y_t is the log-realized volatility of oil price at a monthly frequency. The vector of explanatory variables at a monthly frequency is denoted as X'_t is whilst the vector of weekly returns or realized volatilities is denoted a $X'^{(W)}_{(t)/s}$, where *s=4* is the number of weekly observations at each month. The vector of explanatory variables (X'_t) at the monthly frequency are the lags used in the HAR model. Hence the name of the model is MIDAS-HAR. $\varepsilon_t \sim$ $N(0,\sigma^2_\varepsilon)$, and β, θ_j are vectors of coefficients to be estimated. The p is the dimension of the lag polynomial in the vector parameters θ_j and the k is the number of lagged months to use.

Representing the constructed variable based on the lag polynomial as $\tilde{X}_{\cdot j,t} = \sum_{j=0}^{k-1} X'^{(W)}_{(t-\tau-is)/s}$, the MIDAS model is written as:

$$y_t = X'_{t-i}\beta + \sum_{j=0}^{p} \tilde{X}_{\cdot j,t}\,\theta_j + \varepsilon_t$$

Thus, the number of vector coefficients to be estimated θ_j depends on p and not on the number of daily lags k.

We tested our monthly forecasting ability of the models using both the Mean Squared Predicted Error (MSPE) and the Mean Absolute Percentage Predicted Error (MAPPE), relative to the same loss functions of the monthly no-change forecast.

Results

MIDAS-HAR-RV and MIDAS-HAR-RET forecasting models with weekly exogenous variables are capable of significantly improving the forecast accuracy compared to the no-change model, especially for the horizon from 1-month to 6-months ahead, based on MSPE and MAPPE.

Specifically, the best forecasting improvement is provided by MIDAS-HAR-RV-EXRATE model at 58%, 34% and 7% respectively compared to the no-change forecast for three different horizons (1-month, 3-months and 12-months). Furthermore all MIDAS-HAR-RV and MIDAS-HAR-RET forecasting models with weekly exogenous variables outperform the no-change forecast for the horizon from 1-month to 3-months based on both MSPE and MAPPE for Brent Oil.

Similar to the Brent oil price results, from 1-month to 3-months forecasts, all MIDAS-HAR-RV and MIDAS-HAR-RET forecasting models produce better forecasts relative to the no-change forecast for WTI oil price.

Furthermore, all MIDAS-HAR-RV and MIDAS-HAR-RET models for both Brent and WTI oil have high success ratios to predict the direction of the oil price volatility movements. All our robustness findings confirm the forecasting approaches that we follow in this study is reliable even during turbulent times.

Conclusions

Our findings suggest that when we introduce the HAR model with weekly exogenous variable to MIDAS model, we achieve a better monthly oil price realized volatility forecast,. The realized volatility of trade-weighted US exchange rate against all other currencies is found as the best exogenous variable that helps to improve our monthly oil price volatility forecast relative to the no-change forecast and all other competing models for 1, 3 and 12-months forecast horizons. Moreover, all MIDAS-HAR-RV and MIDAS-HAR-RET models have significant gains in directional accuracy at all horizons for both Brent and WTI oil volatility forecast even during turbulent economic periods. Interestingly, the findings illustrate that Brent oil price is more sensitive than WTI oil price in terms of the responding to financial market information. Based on our outcomes, we suggest that, unlike in the study of Bausmesiter, Guerin and Kilian (2015), there could be substantial losses in ignoring weekly financial data particularly with MIDAS-HAR models when forecasting monthly oil price volatility.

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