OIL PRICE VOLATILITY FORECASTS: WHAT DO USERS NEED TO KNOW?

Stavros Degiannakis, Bournemouth University/Panteion University of Social and Political Science, Stavros.degiannakis@gmail.com
George Filis, Bournemouth University, gfilis@bournemouth.ac.uk

Overview

Oil price volatility forecasting is of major importance due to the financialisation of the oil market over the last 10 years or so and the fact that the oil market participants (e.g. oil-intensive industries, policy makers, portfolio traders) form decisions based on such forecasts. The current practice focuses on predicting the conditional oil price volatility (using daily, weekly or monthly frequency) or the realized volatility (using intraday day). Even more, we observe that the bulk literature evaluates these forecasts using statistical loss-functions, such as the Mean Squared Error.

Nevertheless, oil price volatility users are faced with (i) multiple volatility measures (e.g. historical, implied, realized, conditional, range-based, bipower, semi-variance, two-scale realized) and (ii) different applications for which they use oil price volatility forecasts (e.g. policy making, portfolio allocation, risk management). Thus, in order to make informed decisions, oil volatility users need to know the most appropriate volatility measure in combination with the purpose that the forecast will serve. Hence, we maintain that to achive such aim, the evaluation of the different forecasts using statistical loss functions may not be sufficient. Rather, loss functions that reflect the purpose of the oil price volatility forecast should be employed, i.e. objective-based evaluation functions.

Thus, the aim of this paper is to forecast WTI oil price volatility, focusing on several intraday realized volatility measures, as well as, the OVX, which is the WTI oil price implied volatility index. In particular, the OVX is the 30-day volatility of the United States Oil Fund (USO), which trades WTI futures contracts. We evaluate the forecasts of these volatility measures using objective-based evaluation functions, i.e. based on the forecasts' economic use. In addition, our interest in this paper is on the oil traders, portfolio and risk managers. Thus, forecasts are evaluated based on the after-trading cost profitability of four common trading decisions, namely (i) trading OVX based on the OVX forecasts, (ii) trading OVX based on realized volatility forecasts of the WTI crude oil price, (iii) trading straddles in USO based on OVX forecasts and finally (iv) trading the USO underlying price based on oil price volatility forecasts. We evaluate the after-cost profitability of each forecasting model for 1-trading-day up to 66-trading-days ahead.

Data

This study uses tick-by-tick transaction data of the front-month futures contracts for the WTI and daily data for the OVX index. Our sample period spans from 4th January 2010 until 30th October 2017 (1971 trading days) and it is dictated by the availability of data.

Even more, motivated by Degiannakis and Filis (2017) we also consider four different asset classes as possible predictors for the WTI volatility and OVX. In particular, we also consider tick-by-tick data of the front-month futures contracts for the Brent crude oil, DJ UBS commodity index, Dollar index, S&P500 index, US T-bills. Given that our evaluation functions are also based on trading profits from the United States Oil Fund (USO), we also obtain daily prices for this exchange traded fund.

Our tick-by-tick data are obtained from Tick Data, whereas the data on OVX and USO are retrieved from CBOE and Nasdaq, respectively.

Methods

We use the most well-know realized volatility measures, namely, the Andersen's and Bollerslev's (1998) realized volatility, Hansen' and Lunde's (2005) scaled realized volatily (which captures the close-to-open inter-day volatility), Barndorff-Nielsen' and Shephard's (2004 and 2006) realized bipower variation, Barndorff-Nielsen's et al. (2010) positive and negative realized semi variances, as well as, Andersen's et al. (2012) minimum and median variances.

We consider the following forecasting models. First, we forecast OVX and the 7 realized volatility measures using the random walk and the AR(1) models. Following this, we use Corsi's (2009) Heterogeneous Autoregressive (HAR) model. Furthermore, motivated by Degiannakis and Filis (2017) we use the HAR-X models, where X denotes the exogenous predictors, i.e. the four different asset classes outlined in the data section. Finally, a series of forecast averages are computed for robustness purposes.

The initial sample size for the in-sample estimation of the aforementioned models is 1000 days. We use the remaining 971 days for our out-of-sample forecast evaluation, based on a rolling window approach with fixed window length of 1000 days.

As aforementioned, our trading strategies are (i) trading OVX based on the OVX forecasts, (ii) trading OVX based on realized volatility forecasts of the WTI, (iii) trading straddles in USO based on OVX forecasts and finally (iv) trading the USO underlying price based on oil price volatility forecasts (OVX or realized volatility). The trading criteria for each trading strategy are as follows:

Trading strategy 1: If the OVX forecast is higher (lower) than the current OVX then a trader goes long (short) on OVX.

Trading strategy 2: If the WTI volatility forecast is higher (lower) than the current WTI volatility then a trader goes long (short) on OVX.

Trading strategy 3: If the OVX forecast is higher (lower) than the current OVX then a trader goes long (short) on a straddle.

Trading strategy 4a: If the OVX forecast is higher (lower) than the current OVX then a trader goes short (long) on the USO.

Trading strategy 4b: If the WTI volatility forecast is higher (lower) than the current WTI volatility then a trader goes short (long) on the USO.

Finally, a variant of the Model Confidence Set procedure is employed to identify the set of models that generate superior after-trading cost profits.

Results and Conclusions

Our preliminary findings show quite clearly that objective-based evaluation functions are indeed useful compared to stand alone statistical loss functions, given that depending for which trading strategy the volatility forecast is used, different models and realized volatility measures are useful. For the first trading strategy (OVX trading based on the OVX forecasts), it is the semi-variance measures that generate the highest profitability. The second trading strategy suggests that once again the semi-variance measures generate the highest profitability, yet not greater than those profits from the first strategy. For Straddles it is the realized volatility models that incroporate the forex asset class (dollar index), irrespectively of the realized volatility measures. Finally, for the forth trading strategy (trading USO based on OVX or WTI volatility forecasts) the highest profitability is achieved using OVX forecasts that have as predictors the WTI and Brent oil price volatility, irrespectively of the volatility measure.

References

Andersen, T. & Bollerslev, T. (1998). ARCH and GARCH Models. In (eds.) Kotz, S., Read, C.B. and Banks, D.L., Encyclopedia of Statistical Sciences Vol.II., John Wiley and Sons, New York.

Andersen, T., Dobrev, D. & Schaumburg, E. (2012). Jump-Robust Volatility Estimation Using Nearest Neighbor Truncation. Journal of Econometrics, 169(1), 75-93.

Barndorff-Nielsen, O., Kinnebrock, S., & Shephard, N. (2010). Measuring downside risk – Realised semivariance. In: T. Bollerslev, J. Russell and M. Watson (eds) Volatility and Time Series Econometrics: Essays in Honor of Robert F. Engle. Oxford University Press.

Barndorff-Nielsen, O. & Shephard, N. (2004). Power and bipower variation with stochastic volatility and jumps. Journal of Financial Econometrics, 2(1), 1-37.

Barndorff-Nielsen, O. & Shephard, N. (2006). Econometrics of Testing for Jumps in Financial Economics Using Bipower Variation. Journal of Financial Econometrics, 4, 1-30.

Corsi, F. (2009). A simple approximate long-memory model of realized volatility. Journal of Financial Econometrics, 7, 174–196.

Degiannakis, S. & Filis, G. (2017). Forecasting oil price realized volatility using information channels from other asset classes. Journal of International Money and Finance, 76, 28-49.

Hansen, P.R. & Lunde, A. (2005). A Realized Variance for the Whole Day Based on Intermittent High-Frequency Data. Journal of Financial Econometrics, 3(4), 525-554.