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Forecasting the aggregate oil price volatility in a data-rich environment

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ABSTRACT

This paper explores the effectiveness of a large set of indicators in forecasting crude oil price volatility, including uncertainty and market sentiment, macroeconomic indicators, and technical indicators. Using the OLS, LASSO regression, and various combination forecasts, we obtain several noteworthy findings. First, we determine which indicators most effectively forecast oil price volatility. Specifically, the uncertainty index is notable. Second, in general, combination strategies and LASSO produce statistically and economically significant forecasts. Third, the combined and LASSO strategies perform considerably better during recessions than expansions. Overall, our study provides which indicators and strategies can improve forecasting accuracy in the oil market.

1. Introduction

Crude oil plays an essential role in the world economy. Oil price uncertainty has important macroeconomic effects (Kilian, 2009) and effects on financial markets (Kang et al., 2015). However, how to forecast oil price volatility accurately is a major challenge facing researchers, one that is critical for market participants and policy makers in making correct decisions.

Pan et al. (2017) indicate that a large body of literature has focused on forecasting oil price volatility using historical volatility or prices in the framework of GARCH-class and realized volatility models - for example, Cheong (2009), Agnolucci (2009); Wei et al. (2010), Efimova and Serletis (2014), Ma et al. (2017), Sevi (2014), Prokopczuk et al. (2015), Degiannakis and Filis (2017). In this study, we examine the effectiveness of a large set of indicators in forecasting crude oil price volatility. These indicators include not just historical price information but uncertainty and market sentiment indicators (UMS), macroeconomic indicators (MF), and technical indicators (TE). This study makes four contributions to the literature on oil price volatility forecasting as follows.

First, although previous studies (e.g., Paye, 2012; Christiansen et al., 2012) have primarily examined the link between macroeconomic fundamentals and volatility in the stock market, it is unclear whether these variables are also helpful in forecasting oil price volatility. Answering this question may help investors to select optimal portfolios and manage financial risk. Additionally, it may be useful for macroeconomists, politicians, and decision makers in developing a better understanding of potential indicators of crude oil market volatility.

In this study, we further consider uncertainty and market sentiment indicators and technical indicators in forecasting oil price volatility. There are two primary reasons for this choice. On the one hand, Whaley (2000), Pastor and Veronesi (2012), Baker et al. (2016), Jurado et al. (2015), among others, find that UMS indicators are useful in forecasting volatility. However, many studies have focused on the stock market. In this paper, we use four indexes to represent UMS indicators, namely, the uncertainty index (UI) constructed by Jurado et al. (2015), the economic policy uncertainty index (EPU) proposed by Baker et al. (2016), the oil sentiment index (Deeney et al., 2015) and the Michigan US consumer sentiment index, and we examine their predictive ability with respect to the oil market. On the other hand, Neely et al. (2014) find that technical indicators (TI) significantly predict the sentiment-changes index. Therefore, in this paper, we exploit additional information from TI indicators and investigate their ability to forecast future oil price volatility.

Most of the aforementioned studies focus on the predictive power of volatility models based on historical information (e.g., prices). To the

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best of our knowledge, among existing studies, only a small number investigate numerous indicators of oil price volatility in a data-rich environment. This study begins by investigating the success of various indicators in forecasting oil price volatility and thus provides an overview of their effectiveness.

Second, in this study, we further investigate the effectiveness of the variables referenced in the previous paragraph in predicting oil price volatility during National Bureau of Economic Research (NBER)-dated business cycle expansions and recessions, investigating differences in their relative performance in forecasting oil price volatility. It is worth noting that few studies have investigated the effectiveness of data-rich indicators in predicting oil price volatility, especially across different economic states. Our study provides empirical evidence regarding which indicators are most powerful in forecasting oil price volatility during expansions and recessions and contributes substantially to efforts to forecast volatility in the oil market.

Third, it has been well-documented that the predictive ability of a single model is highly unstable and can change over time (see, e.g., Stock and Watson, 2004; Wang et al., 2016). This motivates us to use a combination of forecasts of a set of models, rather than relying on the forecasts of single models. Forecast combination is described by Bates and Granger (1969) and is considered an effective forecasting method (Clemen, 1989).[2] In this study, we use combination forecasts with constant and time-varying weights to predict future volatility and evaluate forecasting performance. We choose simple combination forecasts with equal weights as constant combinations. In particular, asset price volatility is affected by many uncertain factors, such as economic cycles, political policies, and extreme events, which lead to frequent structural breaks in statistical measures of volatility. To incorporate structural breaks over time into a single model, Raftery et al. (2010) propose the dynamic model averaging (DMA) approach, which allows a model to vary with variables over time. Consequently, DMA has been widely used in forecasting in recent years (e.g., Wang et al., 2016). Thus, we use the DMA method as our time-varying combination method of forecasting oil price volatility. To the best of our knowledge, this study provides new insights into predicting oil price volatility, combining data-rich indicators. Additionally, we examine the effectiveness of the Lasso regression (Tibshirani, 1996) in forecasting oil price volatility. Therefore, we investigate the effectiveness of a large set of indicators in predicting future oil price volatility using various strategies, notably DMA and the LASSO regression.

Fourth, previous studies (e.g., Ma et al., 2018; Pu et al., 2016; Wang et al., 2016; Zhang et al., 2018) find that with respect to forecasting performance, statistical significance is not sufficient to prove the superiority of a specific model, because market investors are more interested in the economic value of volatility models. To date, we find that few papers investigate the economic differences of those aforementioned predictors in the oil market. Therefore, we follow the literature by considering a mean-variance utility investor who allocates his or her assets between oil and the risk-free Treasury bill, where the optimal weight of oil in the portfolio is ex ante determined by volatility and mean forecasts of the oil price return (Zhang et al., 2018). In this article, we seek to answer the following question: Which predictors and strategies can help the investors obtain more economic benefits?

In this paper, we obtain several noteworthy findings. First, in general, most UMS indicators contain significant predictive information, and several MF and TI indicators achieve better forecasting accuracy than our benchmark model. Superior indicators exhibit stable performance during different forecasting windows. Second, combination forecast and LASSO regression strategies, except for the TI indicators, generally outperform the benchmark model. In particular, the DMA strategy can generate better forecasts than other strategies. Third, overall, individual indicators, combination forecasts and the LASSO regression display superior performance in forecasting oil price volatility during recessions compared with expansions. Fourth, in general, some predictors and strategies can not only obtain higher accuracy forecasts, but also have better performance in portfolio. Thus, our study provides evidence regarding which indicators and strategies can increase forecast accuracy in the oil market, information that is useful to investors, practitioners and policymakers in making correct decisions.

The remainder of the paper is organized as follows. Section 2 introduces the volatility model and the volatility indicators. The data and preliminary analysis are presented in Section 3. The empirical forecasting results and a robustness check are presented in Section 4. Section 5 is our economic value. Our conclusions exhibit in Section 6.

2. Volatility model and predictors

In this section, we briefly introduce realized variance, the impact factors (e.g., uncertainty and market sentiment indicators, macroeconomic and financial indicators, and technical indicators), and the volatility model.

2.1. Monthly realized variance

In line with of Paye (2012), Christiansen et al. (2012) and Nonejad (2017), we construct the monthly realized variance as follows:

$$\mathrm{RV}_t = \sum_{j=1}^{N_t} r_{jt}^2, \tag{1}$$

where N_t represents the number of trading days in the t-th month, and r_{jt} indicates the daily return on crude oil prices on the j-th trading day of the t-th month. According to Andersen et al. (2003) and Barndorff-Nielsen and Shephard (2004), as the intra-period sampling frequency increases, Eq. (1) converges in probability to the increment in the quadratic variation of a frictionless, arbitrage-free asset pricing process.

2.2. Impact variables

2.2.1. Uncertainty and market sentiment (UMS) indicators

Uncertainty is typically defined as the conditional volatility of a disturbance that is unforecastable from the perspective of economic agents (Jurado et al., 2015). Uncertainty can increase market fluctuations (Pastor and Veronesi, 2012). Therefore, in this study, we utilize the uncertainty index (UI) constructed by Jurado et al. (2015) and the economic policy uncertainty index (EPU) proposed by Baker et al. (2016) to represent market uncertainty and investigate the effects of uncertainty on future oil price volatility.[3] For example, Liu and Zhang (2015) find that EPU can help forecast S&P 500 index volatility. Additionally, we examine the effectiveness of the sentiment index constructed by Baker and Wurgler (2006) in predicting volatility. More importantly, inspired by Baker and Wurgler (2006), Deeney et al. (2015) use principal component analysis to construct the oil sentiment index (OSI), which includes the volume of oil traded, the historic volatility of oil prices, the put–call ratio of oil options, the ratio of speculative trades to oil demand, and the implied volatility of a local stock market index. In this paper, we use this index to analyze the predictability of the oil markets. Notably, Qiu and Welch (2006) provide evidence that the University of Michigan US consumer sentiment index[4] (CSI) is a good proxy for investor sentiment in the US. As oil is an important commodity in the world, we investigate the predictive power of the CSI index with regard to oil market volatility.

[2] For recent developments in the study of forecast combinations, see the survey of Timmerman (2006).

[3] UI and EPU are available at https://www.sydneyludvigson.com/data-and-appendixes/and http://www.policyuncertainty.com/, respectively.

[4] The CI index can be accessed at https://data.sca.isr.umich.edu/data-archive/mine.php.