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The incremental information content of investor fear gauge for volatility forecasting in the crude oil futures market

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ABSTRACT

This paper aims to investigate whether investor fear gauge (IFG) contains incremental information content for forecasting the volatility of crude oil futures. For this purpose, we use oil volatility index (OVX) to measure the IFG. Adding the IFG to existing heterogeneous autoregressive (HAR) models, we develop many HAR models with IFG. Subsequently, we employ these HAR models to predict the volatility of crude oil futures. The results from the parameter estimation and out-of-sample forecasting show that the in-sample and out-of-sample performances of HAR models with IFG are significantly better than their corresponding HAR models without IFG. The results are robust in different ways. Thus, the HAR models with IFG are more beneficial to the decision making of all participants (including financial traders, manufacturers and policymakers) in the crude oil futures market. More importantly, the results suggest that the investor fear gauge has a significant positive effect on volatility forecasting, and can help improve the performances of almost all the existing HAR models.

1. Introduction

The volatility of financial assets is closely related to portfolio optimization, risk management, and option pricing (see, e.g., Andersen et al. 2017; Billio et al., 2017; Dai and Wen 2018; Moreira and Muir 2017). In the crude oil futures market, volatility plays a vital role in the decision of all participants in the crude oil futures market, including traders, manufacturers, as well as policymakers. Additionally, the volatility of crude oil futures has an important impact on the global economy and financial stability (see, e.g., Charles and Darné 2017; Cheong 2009; Gong and Lin, 2018a; Lin et al., 2014; Wang et al. 2016a; Wen et al. 2018). Thus, understanding the volatility of crude oil futures is vital for oil-related researchers and participants. Among the many issues related to the volatility of crude oil futures, forecasting volatility is one of the major issues that have attracted the attentions of oil market-related researchers and participants.

The existing literature shows that there are ample models based on low-frequency data modeling used for predicting the volatility of crude oil futures. These include historical volatility models (Xu and Ouenniche 2012), AR-type models (Xu and Ouenniche 2012), ARFIMA model (Choi and Hammoudeh 2009), GARCH-type models (Arouri et al. 2012; Manera et al. 2016), SV-type models (Baum and Zerilli 2016), power autoregressive models (Sadorsky and McKenzie 2008), among others. However, it is difficult for the models based on low-frequency data to accurately measure the whole-day volatility information of crude oil futures.

Andersen and Bollerslev (1998) propose a new proxy of volatility using high-frequency data. The proxy variable is named the realized volatility (RV). Corsi (2009) develop a heterogeneous autoregressive model of realized volatility (HAR-RV model) on the basis of the heterogeneous market hypothesis of Müller et al. (1993), and is later extended. On the basis of the HAR-RV model, some researchers propose many new HAR models, such as the HAR-RV-J, HAR-CJ (Andersen et al. 2007), LHAR-RV (Asai et al. 2012), LHAR-RV (Corsi and Renò, 2012), HAR-S-RV-J (Chen and Ghysels 2011) models. The HAR models are some of the most popular models for forecasting volatility in the financial markets. Thus, this paper employs the HAR models to predict the volatility of crude oil futures.

Notably, Chicago Board of Trade (CBOT) proposed the oil volatility index (OVX) in 2007. The OVX can be used to measure the investor fear gauge (IFG) in the crude oil market (see Ji and Fan 2016; Liu et al. 2017). The IFG (or OVX) is closely related to the crude oil futures market. Some studies find that the IFG (or OVX) has an important effect

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on the returns and volatility of crude oil futures (e.g., Aboura and Chevallier 2013; Haugom et al. 2014; Ji and Fan 2016). This paper develops HAR models with IFG to examine whether investor fear gauge contains incremental information content for forecasting the volatility of crude oil futures. The paper mainly has three contributions. First, the paper forecasts the volatility of crude oil futures based on high-frequency data. Using high-frequency data can obtain more accurate estimator for volatility, so our results are more reliable than those obtained using low-frequency data. However, existing literature that predicts the volatility of crude oil futures based on high-frequency data is limited. Thus, our study is an important complement to the literature on volatility forecasting based on high-frequency data.

Second, most of the existing studies investigate the relationship between returns and volatility of crude oil futures and investor fear gauge (e.g., Ji and Fan 2016; Liu et al. 2017). Different from these studies, our study investigates whether investor fear gauge play an irreplaceable role in the prediction of the volatility of crude oil futures. From the parameter estimation and out-of-sample evaluation of the HAR models, we find that investor fear gauge (IFG) contains additional ex ante information for the future volatility of crude oil futures, relative to volatility components, leverage effects and structural breaks. The result means that the IFG should be considered while forecasting the volatility of crude oil futures.

Third, we develop many HAR models with IFG, based on the existing HAR models. The empirical results show that the HAR models with IFG outperform their corresponding HAR models without IFG while forecasting the volatility of crude oil futures. We find that the above results are robust for logarithmic HAR models, after controlling for structural breaks, and other benchmark HAR models. More importantly, we argue that taking account of investor fear gauge (IFG) can help improve the out-of-sample predictive abilities of most of the other existing HAR models (such as the HAR-CSJ model (Sévi 2014), the HAR-RV-type models with regime switching (Ma et al. 2017), the TVP-HAR-RV and TVP-HAR-RV-TCJ models (Wang et al. 2017), besides the HAR models used in this paper. The findings suggest that using the HAR models with IFG can obtain more accurate predicted values of volatility in crude oil futures market, which is more beneficial to the decision of oil market investors, manufacturers and policymakers.

The rest of this paper is structured as follows. Section 2 is the literature review. Section 3 reports the estimations of some volatility components. Section 4 develops six HAR models with IFG, including HAR-RV-IFG, LHAR-RV-IFG, HAR-CJ-IFG, HAR-S-RV-J-IFG, HAR-RV-SJd-IFG, and HAR-RV-ARJ-IFG models. Section 5 presents the data and summary statistics. Section 6 estimates the parameter of the HAR models. Section 7 provides the out-of-sample results for comparing the HAR models without IFG and HAR models with IFG, and investigates the role of investor fear gauge (IFG) in volatility forecasting in the crude oil futures market. Section 8 provides the robustness test for the out-of-sample results. The conclusion is presented in Section 9.

2. Literature review

In this section we mainly review two parts of the literature, including volatility forecasting in the crude oil futures market and the development of HAR models.

2.1. Volatility forecasting in the crude oil futures market

The accurate prediction of volatility has a positive effect on the decision of investors, manufacturers, as well as policymakers in the crude oil futures market. Thus, many researchers pay close attention to volatility forecasting, and attempt to propose new methods to improve the prediction accuracy of existing methods for forecasting volatility in the crude oil futures market.

Most of the existing literatures on forecasting the volatility of crude oil futures are based on low-frequency data. The GARCH-type models are some of the most popular methods for forecasting the volatility of crude oil futures. Sadorsky (2006) find that GARCH model reveals good performance for forecasting volatility in the crude oil futures market. Narayan and Narayan (2007) use GARCH-type models to test the role of regimes and market conditions in forecasting volatilities in four petroleum futures markets. Cheong (2009) show that the simplest GARCH model provides a good forecasting ability for the volatility of Brent crude oil futures. Arouri et al. (2012) indicate that GARCH models with instability and long memory features have good predictive ability for the volatilities of oil spot and futures prices. Hou and Suardi (2012) employ the nonparametric GARCH model to predict the volatilities of Brent and WTI crude oil futures. The results show that nonparametric GARCH model provides better volatility forecasts than parametric GARCH model. Klein and Walther (2016) employ the mixture memory GARCH model to forecast the volatility of Brent and WTI crude oil futures. Lux et al. (2016) combine the Markov-switching multifractal (MSM) method and a battery of GARCH-type models to model and predict volatility in WTI crude oil futures market. Manera et al. (2016) introduce alternative measures of speculation into the variance equation of GARCH model and test the effect of speculation on the volatility of crude oil futures.

In addition to GARCH-type models, some models based on low-frequency data are used to predict the volatility of crude oil futures. For example, Sadorsky and McKenzie (2008) employ power autoregressive models to forecast the volatility of WTI crude oil futures. Choi and Hammoudeh (2009) employ the parsimonious ARMA with short-term processes and ARFIMA models to forecast the volatility of crude oil prices. Xu and Ouenniche (2012) use fourteen forecasting models (including historical volatility models and AR-type models) to forecast the volatility of crude oil prices. Baum and Zerilli (2016) use the stochastic volatility model (SV model) and SV model with jumps (SVJ model) to forecast the volatility of crude oil futures.

In recent years, volatility forecasting models based on high-frequency data have become very important methods for predicting volatility in the financial markets. However, the literature on the forecast of volatility of crude oil futures models based on high-frequency data remains limited. Some representative studies are listed as follows. Haugom et al. (2014) employ the HAR-RV, HAR-RV-IV, HAR-RV-EX and HAR-RV-IV-EX models to forecast the volatility of WTI crude oil futures. Sévi (2014) predict the volatility of crude oil futures using the HAR models (e.g. the HAR-CSJ and HAR-CSJd models). Wen et al. (2016) develop HAR models with structural breaks to predict volatility in the WTI crude oil futures market. Ma et al. (2017) propose the HAR models with regime switching to predict volatility in the WTI crude oil futures market. The above studies find that the HAR models exhibit good performance for predicting the volatility of crude oil futures.

2.2. The development of HAR models

Corsi (2009) uses high-frequency data to calculate the realized volatility (RV, a proxy of volatility), and develops the HAR-RV model. Corsi (2009)'s work greatly improves the use of models based on high-frequency data for forecasting the volatility of financial assets. Lots of studies (e.g., Andersen et al. 2011; Celik and Ergin 2014; Corsi 2009) show that the predictive ability of HAR-RV model is better than the GARCH-type, SV-type and ARFIMA-RV models while predicting the volatility of financial assets.

Furthermore, based on the HAR-RV model, some researchers propose new HAR models to improve the forecasting abilities of models for future volatility. Andersen et al. (2007) decompose the RV of HAR-RV model into continuous sample path variation and discontinuous jump variation and develop the HAR-RV-J and HAR-CJ models. Chen and Ghysels (2011) decompose the RV of HAR-RV model into positive realized semivariance and negative realized semivariance. Also, considering the discontinuous jump variation, they develop the HAR-S-RV-J model. Adding leverage effects to the HAR-RV and HAR-CJ models,