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Forecasting the realized volatility of the oil futures market: A regime switching approach

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ABSTRACT

Considering nonlinear and highly persistent dynamics of realized volatility, we introduce Markov regime switching models to the Heterogeneous Autoregressive model of the Realized Volatility (HAR-RV) models to forecast the realized volatility of the crude oil futures market. In-sample results demonstrate that the high volatility regime is short-lived. Out-of-sample results suggest that HAR-RV models with regime switching increase the forecasting ability significantly than those without regime switching. Moreover, these findings are robust for different actual volatility benchmarks, forecasting windows, and model settings.

1. Introduction

Oil is an important energy commodity that plays an essential role in the world economy. Oil price volatility has a significant macroeconomic influence to the real economy (Hamilton, 1983, 2003; Kilian and Park, 2009) and financial markets (Aloui and Jammazi, 2009; Kilian and Park, 2009). Oil price volatility is also an important issue for risk management, derivative pricing, portfolio selection, and many other financial activities. Thus, modeling and forecasting the volatility of crude oil price is critical for researchers, market participants, and policymakers.

Modeling and predicting oil price volatility are investigated based on the framework of the GARCH-class models (e.g., Agnolucci, 2009; Cheong, 2009; Kang et al., 2009; Mohammadi and Su, 2010; Wei et al., 2010; Nomikos and Pouliasis, 2011; Nomikos and Andriosopoulos, 2012; Wang and Wu, 2012; Efimova and Serletis, 2014). However, GARCH-class models are constructed for daily or even a lower frequency data, which can result in a substantial loss of intraday trading information. Because of the availability of abundant high-frequency (intraday) data in recent years, research on financial market volatility has taken new avenues. Moreover, high-frequency data contains a wealth of information that can help market participants to make quicker decisions. As a result, volatility measure based on high-frequency data has received much attention in academia.

The seminal work on measuring volatility using high-frequency data by Andersen and Bollerslev (1998) proposes the realized volatility or variance[1] (RV), which is robust to market microstructure effects. For a given fixed interval, RV is defined as the sum of squared returns over non-overlapping intervals. Thus, RV can directly be observed, and it enables researchers to gauge the level of RV and understand its dynamics. The early study on describing and predicting RV is based on the autoregressive fractionally integrated moving average (ARFIMA) model proposed by Andersen et al. (2003). Although the ARFIMA model achieves a higher forecast accuracy than GARCH-class models (e.g., Koopman et al., 2005; Liu and Wan, 2012), Corsi (2009) points out that the ARFIMA model is just a convenient mathematical trick, lacks a clear economic interpretation, and leads to the loss of information on a vast number of transactions. Corsi (2009) also constructs a simple

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[1] We will use the terms realized volatility and realized variation (variance) interchangeably.

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heterogeneous autoregressive model of the realized volatility (HAR-RV), which can capture "stylized facts" in the financial markets, such as long memory and multi-behavior. As a result, HAR-RV model is commonly employed to forecast the volatility using high-frequency data.

Studies on forecasting volatility using high-frequency data have mainly concentrated on the stock and exchange rate markets (e.g., Andersen et al., 2007a; Corsi et al., 2010; Bekaert and Hoerova, 2014; Bollersleva et al., 2015; Degiannakis, 2008; Duong and Swanson, 2015; Wang et al., 2016). Nevertheless, to the best of our knowledge, there are insufficient studies on forecasting the oil futures price volatility using high-frequency data. For example, Degiannakis and George (2016) point out that studies, such as Haugom et al. (2014), Sévi (2014), Prokopczuk et al. (2016), and Wen et al. (2016), try to forecast oil price volatility using ultra-high frequency data. Therefore, in this research, as a first step, we use the HAR-RV model and its various extensions to forecast the realized volatility of the oil futures price. To be precise, we label those twelve models as HAR-RV-type models, which include: HAR-RV (Corsi, 2009), HAR-RV-J and HAR-RV-CJ (Andersen et al., 2007a, 2007b), HAR-RV-TJ (Corsi et al., 2010), HAR-S-RV-J (Chen and Ghysels, 2011), HAR-RV-PS2 and HAR-RV-PS3 (Patton and Sheppard, 2015), HAR-CSJ and HAR-CSJd (Sévi, 2014), HAR-ARJ (Prokopczuk et al., 2016), HAR-RV-JLM and HAR-S-RV-J-JLM (Liu et al., 2016).

HAR-RV-type models are linear, and the estimated coefficients of those models are constant. However, Granger and Ding (1996) find out that persistence in volatility is usually non-constant over time. Previous studies (e.g., Longin, 1997; Raggi and Bordignon, 2012; Goldman et al., 2013; Ma et al., 2015) provide evidence that a higher level of persistence exists when volatility is low, implying the presence of nonlinearities. Moreover, it is well known that due to many factors, such as business cycle, major events, and economic policy, the statistical property of volatility (e.g., volatility persistence) always undergoes structural breaks (e.g., Banerjee and Urga, 2005; Wahab and Lee, 2009) or switches between different regimes (Hamilton and Susmel, 1994). Therefore, it is appropriate to use a model with regime switching to describe volatility dynamics. For example, Goldman et al. (2013) use threshold autoregressive fractionally integrated moving average (TARFIMA) models with regime switching and show that TARFIMA achieves a higher forecast accuracy than ARFIMA. Raggi and Bordignon (2012) find that introducing nonlinearities leads to a better prediction for several forecast horizons. Though it is the fact that considering nonlinear and highly persistent dynamics of realized volatility can significantly improve the forecasting performance, a little has been done on forecasting realized volatility by using HAR-RV-type models with regime switching. Therefore, we introduce regime-switching characteristics to the HAR-RV-type models and examine whether HAR-RV-type models with regime switching can forecast better than HAR-RV-type models without regime switching. In regime switching models, one of the aspects is deciding the number of regimes. Similar to the existing studies, such as Bekaert et al. (2015), Goldman et al. (2013), Ma et al. (2015), Raggi and Bordignon (2012), Shi and Ho (2015), and Wang et al. (2016), we also consider two regimes: low volatility regime and high volatility regime.

The aim of this paper is to forecast the realized volatility of the crude oil futures price using HAR-RV models and their extensions. This research contributes to the literature of modeling realized volatility in two ways: (a) to forecast the realized volatility of the oil futures market, we consider the nonlinear and highly persistent dynamics of realized volatility, combine HAR-RV-type models with the regime switching, and construct new volatility models, which can provide a new perspective to model and forecast the volatility of the oil futures. Furthermore, the proposed models are instrumental since Nomikos and Pouliasis (2011) point out that a regime-switching model may be more suitable for modeling volatility, particularly in energy markets, where structural breaks are quite common, because oil market volatility is characterized by different dynamics under different market conditions. For instance, Fong and See (2002, 2003) document a strong evidence of regime switching in the temporal volatility dynamics of oil futures, consistent with the theory of storage. Nomikos and Pouliasis (2011) also state that an increase in backwardation is more likely to increase regime persistence in the high volatility state due to low inventories; and (b) evaluating the forecasting ability of HAR-RV-type models with regime switching, we find that those models can gain greater accuracy in prediction and that further promotes the applications of those models to forecast the realized volatility using the ultra-high frequency data. Moreover, the proposed HAR-RV-type models with regime switching can also be applied to forecast the future volatility of the other markets, such as stock and exchange markets.

In this paper, we compare the forecasting performance HAR-RV-type models and their extensions with regime switching based on the model confidence set (MCS) test under HMSE and HMAE loss functions. In-sample results show that the negative semi-variation has a significantly positive impact on the realized volatility, implying that the negative semi-variance contributes more to the realized volatility. Also, the high volatility regime is short-lived. Out-of-sample empirical results indicate that introducing the regime-switching behavior of daily realized volatility in HAR-RV-type models leads to greater forecast accuracy. Our results also show that the same findings are valid for another volatility benchmark - realized kernel (RK) (e.g., Barndorff-Nielsen et al., 2008) and different forecasting windows. We further consider high and low volatility regimes for all variables in volatility models and warrant that regime switching can significantly help in forecasting.

The rest of the paper is organized as follows: Section 2 describes the volatility measures and models. The methodology of out-of-sample forecasting and the Model Confidence Set (MCS) test are discussed in Section 3. Section 4 provides the data and some preliminary analysis. The empirical forecasting results are presented in Section 5. Section 6 concludes the paper.

2. Volatility models

Section 2 briefly describes several popular volatility measures based on intraday high-frequency data and the corresponding extended models with regime switching capturing the volatility dynamics.

2.1. Realized volatility and realized bi-power variation measures

The primary interest is to measure the daily variance of oil futures returns, which will be estimated from the realized variance. For a given day t, we divide the time interval, which is considered as [0, 1], into n subintervals of length, where $n = 1/\Delta$ and Δ is the sampling frequency. Consequently, the realized volatility can be defined as the sum of all available intraday high-frequency squared returns and given by,

$$RV_t = \sum_{j=1}^{1/\Delta} r^2_{(t-1)+j^*\Delta,\Delta} \tag{1}$$

where $r_{(t-1)+j^*\Delta,\Delta}$ represents the intraday returns. According to Barndorff-Nielsen and Shephard (2004), when $\Delta \to 0$, RV can be expressed as:

$$RV_t \to \int_0^t \sigma^2(s)ds + \sum_{0<s\le t} \kappa^2(s) \tag{2}$$

where $\int_0^t \sigma^2(s)ds$ is called as the integrated variance computed by realized bi-power variation (BPV), which can be defined as:

$$BPV_t = u_1^{-2} \sum_{j=2}^{1/\Delta} |r_{(t-1)+j^*\Delta,\Delta}||r_{(t-1)+(j-1)*\Delta,\Delta}| \tag{3}$$

where $u_1 \simeq 0.7979$. $\sum_{0<s\le t} \kappa^2(s)$ is the discontinuous jump part of the quadratic variation (QV) process. Let $J_t = \sum_{0<s\le t} \kappa^2(s)$ and that can be written as $J_t = \max(RV_t - BPV_t, 0)$ (Barndorff-Nielsen and Shephard, 2004; Andersen et al., 2007a, 2007b).