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Forecasting the realized range-based volatility using dynamic model averaging approach

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ABSTRACT

In this study, we forecast the realized range-based volatility (RRV) using the heterogeneous autoregressive realized range-based volatility (HAR-RRV) model and its various extensions, which are called HAR-RRV-type models. We first consider the time-varying property of those models' parameters using the dynamic model averaging (DMA) approach and evaluate the forecasting performance of three types: individual HAR-RRV-type models, combined models with constant weights, and combined models with time-varying weights. Our out-of-sample empirical results show that combined models with time-varying weights can not only generate more accurate forecasts, but also beat individual models and combined models with constant weights.

1. Introduction

The volatility of financial asset and commodity price representing their price uncertainty has a huge strategic importance in risk management, derivative pricing, and portfolio selection. For example, crude oil is traded in the global market and its price uncertainty has significant effect on economic growth and financial market all around the world (see, e.g., Hamilton, 1983; Kilian, 2006; Aloui and Jammazi, 2009; Kilian and Park, 2009). Therefore, modelling and forecasting volatility of asset price are crucial to financial market participants and policy makers.

A large number of studies focus on modelling and forecasting volatility of financial and commodity markets using low-frequency data (e.g., Agnolucci, 2009; Cheong, 2009; Wei et al., 2010; Mohammadi and Su, 2010; Nomikos and Andriosopoulos, 2012; Charles and Darné, 2014; Efimova and Serletis, 2014; Lean and Smyth, 2015). As high-frequency data carries more information, it can help make better decisions. With the increasing availability of high-frequency data, research on measuring and modelling the volatility based on high-frequency data becomes popular.

For measuring volatility of high-frequency data, Andersen and Bollerslev (1998) propose the realized volatility (RV), which is defined as the sum of non-overlapping squared returns within a fixed time interval. Corsi (2009) proposes a simple heterogeneous autoregressive model of realized volatility (HAR-RV) model. This model is popularly employed in forecasting volatility and shows its outstanding performance in capturing "stylized facts" in financial market, such as long memory and multi-scale behavior of volatility (Andersen et al., 2007; Corsi et al., 2010; Bekaert and Hoerova, 2014; Duong and Swanson, 2015; Bollerslev et al., 2016). Following Corsi (2009), some extensions of HAR-RV model are developed (Andersen et al., 2007; Huang et al., 2016). For example, HAR-RV-J model is proposed by adding the jump component in volatility and HAR-RV-CJ model is developed to investigate the contribution of jumps by decomposing realized volatility into continuous sample path and significant jump components (Andersen et al., 2007). These extensions are mainly based on different decompositions of realized volatility. Moreover, by introducing leverage terms related to negative returns, McAleer and Medeiros (2008) extend HAR-RV model to the leverage HAR-RV (LHAR-RV) model. Recently, some empirical studies show overnight information has a significant impact on volatility and thus can improve the predictability of HAR-type models (e.g., Taylor, 2007; Todorova and Souček, 2014). Overall, HAR-type models perform better than GARCH-class models in capturing the volatility dynamics and are more widely used in high-frequency data (see, e.g., Andersen et al., 2003; Hansen and Lunde, 2005; Koopman et al., 2005; Wei et al., 2010; Çelik and Ergin, 2014; Ma et al., 2015).

Nevertheless, Bandi and Russell (2008) point out that RV could not identify the daily integrated variance of the frictionless equilibrium price in the presence of market microstructure noise. Thus, Martin and

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Dick (2007) introduce another measure called the realized range-based volatility (RRV), which is calculated by the difference between the largest and lowest prices that are observed during a certain period. The measurement precision of RRV is proved to be up to five times greater than the RV. Since the extremes are obtained from the entire price process, RRV carries more information and also relatively less contaminated by noise than realized volatility at fixed intervals. RRV has already been applied in financial assets and it successfully captures the long-term memory behavior in volatility (e.g., Tseng et al., 2009). Some models, such as HAR-RRV and HAR-RRV-RBV-ONI model, are constructed based on RRV and show good out-of-sample forecasting performances (Tseng et al., 2012). Since RRV is much more efficient and sufficient in volatility modelling and forecasting, we choose RRV to measure the volatility of financial assets.

Although, many individual models, such as GARCH-class models and HAR-type models, have been presented, it has also been well documented that the predictability of an individual model is very unstable and changing over time (e.g., Stock and Watson, 2004). Hence, some studiesdiscuss how to combine a set of forecasts to produce superior composite forecasts (Liu and Maheu, 2008; Santos and Ziegelmann, 2014). The existing literature shows that a combined model performs better than an individual model.

In addition, asset volatility is affected by many uncertain factors, such as economic cycles, political policies, and extreme events, which will lead to frequent structural breaks in the statistical property of volatility (e.g., Granger and Hyung, 2004; Liu and Maheu, 2008). To deal with structural breaks over time in a single model, Raftery et al. (2010) propose the dynamic model averaging (DMA) approach, which allows the model vary with the variables over time. Consequently, DMA is widely implemented to forecast inflation, gold price, oil price, and combine the forecasts (Koop and Korobilis, 2012; Aye et al., 2015; Naser, 2016; Wang et al., 2016). DMA approach combines the generated models dynamically by using two forgetting factors to approximately estimate both the model parameters and model switching probabilities, i.e., DMA successfully avoids arbitrary choices made by the model users. However, there is no study of realized range-based volatility dynamics which are described in a time-varying parameter framework such as dynamic model averaging. In order to fill this gap, we first incorporate DMA approach into RRV framework for forecasting volatility of crude oil futures and the S & P 500 index.

The validity of forecasting models is usually evaluated by various methods including loss functions, mean mixed statistics (MME), superior predictive ability (SPA) test, and advanced model confidence set (MCS) test (Brailsford and Faff, 1996; Hansen, 2005; Hansen et al., 2011). Among them, the MCS test has several attractive advantages. MCS test does not require a benchmark and allows for the possibility of more than one "best" models. Thus, we apply MCS as a main criterion for model evaluation.

To the best of authors' knowledge, this study is the first attempt to incorporate DMA approach into RRV framework. Thus, both the time-varying property of high-frequency volatility and time-varying weights of different models are considered over time. In order to forecast the realized range-based volatility of financial assets, we construct five individual HAR-RRV-type models (HAR-RRV, HAR-RRV-J, HAR-RRV-CJ, LHAR-RRV-CJ, and HAR-RRV-ONI), their combinations with constant weights, and their combinations with time-varying weights by applying the DMA approach. Finally, we assess their predictive abilities by using error statistics, MME test, and MCS test.

The contributions of this research are threefold. First, we model the time-varying volatility and compare the models' forecasting ability in the framework of RRV, since the RRV carries more information than RV. We also provide the performance of the models for forecasting RRV across crude oil futures and the S & P 500 index. Second, individual HAR-RRV-type models are unstable over time. However, there is no study on incorporating time-varying combined models with the framework of RRV. Hence, we employ several combined models with constant weights and combined models time-varying weights obtained from DMA to capture the dynamics of volatilities. Third, our empirical study evaluates three types of models (individual HAR-RRV-type models, combined models with constant weights, and combined models with time-varying weights) in forecasting volatility based on error statistics, mean mixed statistics (MME), and MCS test for 5-min, 10-min, and 15-min high-frequency data. Our empirical studies show that DMA approach performs the best. Especially, DMA shows its strength for forecasting RRV based on 5-min frequency data of oil futures.

The rest of this paper is organized as follows. Section 2 briefly describes the specifications of the volatility measure and five individual models based on RRV. Section 3 presents the high-frequency data. Section 4 discusses the in-sample evaluations and out-of-sample forecasting results. Section 5 concludes the paper.

2. Methodology

The volatility measure and forecasting methodology are introduced in this section. Section 2.1 describes the measure of realized range-based volatility (RRV). Based on RRV, HAR-RRV model and its extensions are specified in Section 2.2. Section 2.3 presents the combined models and Section 2.4 discusses applying DMA approach as a combined model with time-varying parameter in RRV framework.

2.1. Realized range-based volatility measure

Using the extreme value method of intra-day return by the high-low range, Martin and Dick (2007) provide a more efficient measure called the realized range-based volatility (RRV), which uses the high-low range instead of the squared return. In their study, RRV significantly improves over RV due to the price range of intraday carrying more information than the closing prices. In order to deal with microstructure issues, we can use a bias-correction procedure to account for the effects of microstructure frictions based upon scaling the realized range with the average level of the daily range. The RRV has been proved to have a lower mean-squared error than RV by simulation experiments (Martin and Dick, 2007). Their result shows RRV is robust to microstructure noise.

Initially, assuming that the oil futures price, p_t, follows a geometric Brownian motion, considering the equidistant partition $0{=}t_0 < t_1 < \ldots < t_M{=}1$, where $t_i{=}i/M$,$t_{i-1} \le t$, $s \le t_i$, and $\Delta{=}1/M$, the intraday range at sampling times t_{i-1} and $t_i (i = 1,2, \ldots, M)$ is

$$s_{p,\Delta i}{=}\sup\{p_t - p_s\}. \tag{1}$$

The estimator RRV for the interval [0, 1] can be expressed as:

$$RRV_t^{\Delta} = \frac{1}{\lambda_{2,m}} \sum_{j=1}^{1/\Delta} s^2_{(t-1)+j*\Delta,\Delta}, \tag{2}$$

where $\lambda_{r,m} = \mathbf{E}(s^r_{w,m}).\lambda_{r,m}$ is the r_{th} moment of the range of Brownian motion over a unit interval. When $\triangle \to 0$, realized range-based volatility (RRV) and the realized range-based bi-power variation (RBV) are specified as below (Christensen and Podolskij, 2006; Christensen and Podolskij, 2007):

$$RRV^{\Delta}_{t,m} \to \int_0^t \sigma^2(s)ds + \frac{1}{\lambda_{2,m}} \sum_{0<s\le t} k^2(s). \tag{3}$$

$$RBV_{t,m} = \frac{1}{\lambda^2_{1,m}} \sum_{j=2}^{1/\Delta} |s_{(t-1)+j*\Delta}||s_{(t-1)+(j-1)*\Delta}| \to \int_0^t \sigma^2(s)ds. \tag{4}$$

From the Eqs. (3) and (4), we have,

$$RRV_{t,m} = \lambda_{2,m} RRV^{\Delta}_{t,m} + (1{-}\lambda_{2,m}) RBV_{t,m} \to \int_0^t \sigma^2(s)ds + \sum_{0<s\le t} k^2(s), \tag{5}$$

where $\int_0^t \sigma^2(s)ds$ represents continuous path component and

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