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An approximate long-memory range-based approach for value at risk estimation

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ABSTRACT

This paper proposes new approximate long-memory VaR models that incorporate intra-day price ranges. These models use lagged intra-day range with the feature of considering different range components calculated over different time horizons. We also investigate the impact of the market overnight return on the VaR forecasts, which has not yet been considered with the range in VaR estimation. Model estimation is performed using linear quantile regression. An empirical analysis is conducted on 18 market indices. In spite of the simplicity of the proposed methods, the empirical results show that they successfully capture the main features of the financial returns and are competitive with established benchmark methods. The empirical results also show that several of the proposed range-based VaR models, utilizing both the intra-day range and the overnight returns, are able to outperform GARCH-based methods and CAViaR models.

1. Introduction

Since the first appearance of value at risk (VaR) in the 1980s, it has become the most prevalent risk measure, and is currently a standard tool for risk management in financial and insurance institutions (Berkowitz, Christoffersen, & Pelletier, 2011; Nieto & Ruiz, 2016). The VaR is the quantile of the conditional distribution of the return on a portfolio. Accurate forecasting of VaR is of great importance for internal risk control and financial regulation. Although the concept of VaR is not complex, its measurement has proved to be challenging. There has been a variety of approaches proposed for the forecasting of VaR, and yet no consensus has been reached as to the best method.

Classical approaches to VaR forecasting, such as the use of generalized autoregressive conditional heteroskedasticity (GARCH) models, historical simulation and conditional autoregressive value at risk (CAViaR) models (Engle & Manganelli, 2004), use only the historical returns. Intra-day data is becoming increasingly available, and it has been found to provide useful information for the estimation of the distribution of the daily returns (Corsi, Mittnik, Pigorsch, & Pigorsch, 2008). Therefore, efforts have been made to use intra-day data in the forecasting of VaR for daily returns. Realized volatility, which is a nonparametric measure of unobservable volatility, calculated using intra-day data, has been widely used as a basis for forecasting daily volatility (see, for example, Andersen & Bollerslev, 1998; Andersen, Bollerslev, Diebold, & Labys, 2001; Barndorff-Nielsen, 2002). However, intra-day data tends to be expensive, and often a long time series of observations is not available. Moreover, the effort and resources required to process the high-frequency data may prove excessive (Rogers & Zhou, 2008).

In contrast, the daily opening, daily closing, intra-day low and intra-day high series for the last thirty years are readily available for most tradable assets. Instead of using intra-day data to produce the realized volatility for VaR estimation, we consider an alternative use of intra-day data, which is much easier to implement and yet highly efficient. We base VaR estimation on the intra-day range,

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which is the difference between the daily high and the daily low log prices. Despite the fact that the intra-day range has been widely studied in volatility forecasting (Andersen & Bollerslev, 1998; Brandt & Jones, 2006; Parkinson, 1980), little attention has been devoted to utilizing the intra-day range in VaR estimation. The only such literature, that the authors are aware of, are the studies of Brownlees and Gallo (2010), Chen, Gerlach, Hwang, and McAleer (2012) and Fuertes and Olmo (2013). Brownlees and Gallo (2010) use the intra-day range in a parametric framework. Chen et al. (2012) consider the use of the intra-day range in CAViaR models. Fuertes and Olmo (2013) includes the intra-day range in a GARCH model. Another variable that we consider in this paper is the market overnight return. It has been pointed out that the overnight return is useful for volatility forecasting, because, while the market is closed, a great amount of highly relevant information arrives from markets abroad, and public announcements might be made after the previous day's closing time (Tsiakas, 2008). The work of Brownlees and Gallo (2010) is the only study that has compared the performance of the intra-day range and realized volatility for VaR estimation, with only parametric methods being considered. The authors are not aware of any study that evaluates the performance of the overnight return for VaR estimation.

This paper has two contributions. First, we propose a number of new quantile regression models based on realized volatility, the intra-day range and the overnight return. Second, we carry out an empirical comparison between the proposed methods and a large number of benchmark methods. Moreover, this paper is the first study that compares VaR estimation performance of a large set of methods based on the intra-day range and methods based on realized volatility for VaR estimation.

The remainder of the paper is structured as follows. Section 2 reviews intra-day volatility measures. Section 3 gives a brief review of the established VaR methods, with particular focus on those that are closely related to our new proposals. Section 4 introduces our new VaR models. Section 5 uses 18 series of stock returns to evaluate the performance of the new models, and to compare their VaR estimation accuracy to established methods. Section 6 provides a summary and some concluding remarks.

2. Intra-day volatility measures

In this section, we introduce the intra-day volatility measures that are used in this study. A very popular intra-day volatility measure is realized volatility. The realized volatility of a certain stock is defined as follows:

$$RV_t = \sqrt{\sum_{i=1}^{M} (P_{t,i\cdot\Delta} - P_{t,(i-1)\cdot\Delta})^2} \tag{1}$$
$$\Delta = \frac{S}{M}$$

where RV_t denotes the realized volatility within day t, S denotes the interval span of market opening hours, Δ divides S equally into M intervals, and $P_{t,i\cdot\Delta}$ denotes the log price at time $i\cdot\Delta$ of day t. It has been theoretically shown that, if the prices $P_{t,i\cdot\Delta}$ are observed without noise, then expression (1) is a consistent estimate of the daily volatility as M tends to infinity (Andersen et al., 2001; Barndorff-Nielsen, 2002). It has been found that models incorporating the realized volatility can significantly improve daily volatility forecasts in comparison to the conventional GARCH models, which are applied to daily returns data (see, for example, Corsi et al., 2008; Hansen, Huang, & Shek, 2012; Martens, Van Dijk, & De Pooter, 2009; Shephard & Sheppard, 2010).

The calculation of realized volatility clearly requires access to high-frequency data. Although such data is gradually becoming available, it is still expensive and is not available for a long time series of observations. The calculation of expression (1) requires significant computational power. Moreover, microstructure noise might contaminate the data, making expression (1) an inconsistent estimate for daily volatility (Andersen, Bollerslev, & Meddahi, 2011). This prompts consideration of, as an alternative intra-day volatility measure, the intra-day range, which is readily available for most tradable assets and requires little computing resource. The intra-day range is defined as follows:

$$Range_t = H_t - L_t \tag{2}$$

where H_t and L_t denote respectively the highest log price and the lowest log price of the day. The intra-day range has been widely studied in volatility estimation. Parkinson (1980) shows that the properly scaled intra-day range is an unbiased estimator of daily volatility, and is more efficient than the squared daily return. Brandt and Jones (2006) show that the efficiency of the intra-day range is even comparable to that of realized variance calculated using 3-hour to 6-hour returns. Alizadeh, Brandt, and Diebold (2002) show that the intra-day range is more robust to market microstructure noise, in comparison with realized volatility.

It should be noted that both the realized volatility and the intra-day range ignore the market overnight return, which is defined as follows:

$$y_{N,t} = open_t - close_{t-1} \tag{3}$$

where $open_t$ denotes the log opening price, and $close_{t-1}$ denotes the log closing price on the previous day. The overnight return has raised the interest of volatility forecasters. Hansen and Lunde (2006) find that an intra-day volatility measure that ignores the overnight return might not be a good proxy for the true daily volatility. Ahoniemi and Lanne (2013) find that incorporating the overnight return can lead to a more accurate realized volatility measure and can influence the relative performance of different volatility forecasting models. Wang, Wu, and Xu (2015) find that including the overnight return along with other explanatory variables improves volatility forecasts from the heterogeneous autoregressive model of realized volatility (HAR-RV) of Corsi (2009). In this paper, we consider the approach of Blair, Poon, and Taylor (2001) and Hua and Manzan (2013), which incorporates the overnight return in the realized volatility as follows:

$$RV_{N,t} = \sqrt{(RV_t)^2 + (y_{N,t})^2} \tag{4}$$

We can also incorporate the overnight return in the intra-day range, as in expression (5). To our knowledge, this