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Detecting sudden changes in volatility estimated from high, low and closing prices

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ABSTRACT

In this paper, we assess the size and power properties of Inclan and Tiao's (1994) Iterated Cumulative Sum of Squares (IT ICSS) algorithm for detecting sudden changes in volatility. We make use of the variance estimator that utilizes high, low and closing prices proposed by Rogers and Satchell (1991) (RS) and compare it with the performance of the demeaned squared returns. We find that the IT ICSS algorithm exhibits more desirable size and power properties when applied with the RS estimator in comparison to the demeaned squared returns. On the empirical side, we apply the IT ICSS algorithm with the RS estimator and demeaned squared returns of the S&P 500, CAC 40, FTSE 100, IBOVESPA and SZSE Composite indices to detect sudden changes in volatility of both developed and emerging markets. We find that most of the structural breaks detected by the RS estimator can be related to major macroeconomic events while very few of the structural breaks detected by demeaned squared returns can be related to macroeconomic events and hence are probably spurious.

1. Introduction

The study of volatility is of considerable interest because of its importance in portfolio allocation, risk management (e.g., for value at risk and expected shortfall), derivatives pricing, futures hedging, trading strategies and asset pricing. Volatility is considered to be an important ingredient of quantitative finance and there exists a plethora of literature for modeling it. If we want to estimate daily volatility using daily closing prices, the most widely used estimator is the squared daily return (demeaned). But this estimator is very noisy as argued by Alizadeh et al. (2002). An alternative way of estimating volatility, with more precision, is to use intraday high frequency data. However, in many cases, high frequency data is not available at all or sometime it is available only over smaller intervals. High frequency data is generally very expensive and requires considerable computational resources for analysis. High frequency data also suffers from market microstructure issues which make volatility estimation using high frequency data highly complex (Dacorogna et al., 2001).

Several studies have highlighted the importance of volatility estimators that utilize the opening, high, low and closing prices of an asset because they give rise to much more efficient estimators of volatility compared to volatility estimated using conventional return data (Garman and Klass, 1980; Parkinson, 1980; Rogers and Satchell, 1991; and Yang and Zhang, 2000). Among them, the RS estimator proposed by Rogers and Satchell (1991) stands out because it is the only one that is unbiased regardless of the drift parameter whereas all others are biased in one way or another if the mean return (drift) is non-zero.[2] The opening, high, low and closing prices are also readily available for most of the traded assets and indices in financial markets and potentially contain more information for estimating volatility when compared to the close to close return data that is conventionally made use of.

Volatility of asset prices may be affected substantially by infrequent structural breaks or regime shifts due to macroeconomic and political events. Inclán and Tiao (1994) propose the Iterated Cumulative Sum of Squares (ICSS) algorithm, referred as IT ICSS hereafter, to detect structural breaks in the unconditional variance of a random process. The IT ICSS test assumes that the zero mean returns are independent over time and normally distributed. The IT ICSS test has been extensively used in detecting sudden changes in the volatility of time series (see, for example, Aggarwal et al., 1999; Malik, 2003; Fernandez and Arago, 2003; Malik et al., 2005). The IT ICSS test detects both a significant increase and decrease in volatility and, hence, can help in identifying both the beginning and the ending of volatility regimes.[3]

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2 The unbiasedness of the Yang and Zhang (2000) estimator follows from that of the RS estimator.

3 Aggarwal et al. (1999), Hammoudeh and Li (2008), Malik (2003), Malik et al. (2005), and Wang and Moore (2009) use demeaned squared returns in detecting sudden breaks in the unconditional variance. Aggarwal et al. (1999) apply the ICSS algorithm on some emerging market indices for the period from 1985 to 1995, and find that volatility shifts are impacted mainly by the local macroeconomic events and the only global event over the sample period that affected several emerging markets was the October 1987 stock market crash in the United States. Fernandez and Arago (2003) utilize the ICSS algorithm to detect structural changes in the variance for European stock indices and their findings are in confirmation with the findings of Aggarwal et al. (1999) that the markets not only react to local economic and political news, but also to news originating in other markets.

Parkinson (1980) finds that the squared difference of the high and the low is proportional to the variance of the time series and introduces an estimator of volatility based on the trading range. Garman and Klass (1980) propose an unbiased estimator of volatility in case of zero drift based on a quadratic function of the high, low and closing prices. Beckers (1983) tests the predictive power of the high-low volatility estimators in comparison with the close to close measure and finds that the daily trading range contains new and important information of the stock price variability and suggests an adjustment procedure to enhance its practical relevance. Rogers and Satchell (1991) propose an estimator of variance in the context of the Brownian motion, based on the high and the low that is unbiased regardless of the drift parameter. Rogers et al. (1994) present an empirical application of the RS estimator. Yang and Zhang (2000) introduce a related volatility estimator based on multiple periods of high, low, opening and closing prices and show that the new volatility estimator is unbiased in the continuous limit, independent of both the drift and the opening price jumps. Alizadeh et al. (2002) propose the use of range based volatility measures in the estimation of stochastic volatility. They show theoretically, numerically, and empirically that range-based volatility measures are highly efficient and approximately Gaussian and are also robust to microstructure noise. Brandt and Diebold (2006) propose a range-based covariance estimator as a step towards estimating volatility in the multivariate case and show that unlike other existing univariate and multivariate volatility measures, the range-based estimator of volatility is highly efficient and robust to market microstructure noise due to bid-ask bounce and asynchronous trading.

The central aim of this paper is to examine the performance of the RS estimator and squared return (demeaned) in detecting sudden changes in volatility using Inclán and Tiao's (1994) (IT) ICSS algorithm by means of Monte Carlo simulation experiments. We study the size and power properties of IT ICSS test for both the volatility proxies for various data generating processes like the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model, the Autoregressive Conditional Heteroskedasticity (ARCH) model and the stochastic volatility (SV) process and also i.i.d. random numbers from the Gaussian, Student t, double exponential and gamma-mixture distributions. The power properties are studied by incorporating sudden breaks of various levels at 25th percentile, 50th percentile and 75th percentile of the data series. Earlier studies related to detecting sudden breaks in volatility or regime shifts have considered demeaned squared return as the input in the IT ICSS algorithm. In this paper, we suggest the use of the RS estimator for measuring the unconditional variance to detect sudden breaks in volatility using the IT ICSS algorithm because it exhibits better size and power properties than demeaned squared returns.

The remainder of this paper is organized as follows: Section 2 introduces the IT ICSS algorithm and the procedure for implementing the RS estimator based extension of the IT ICSS algorithm. In Section 3, we undertake Monte Carlo simulation experiments to assess the IT ICSS algorithm based on the RS estimator and demeaned squared returns. Section 4 describes the application of the RS estimator in detecting sudden breaks in S&P 500, FTSE 100, CAC 40, IBOVESPA and SZSE Composite indices and Section 5 concludes with a summary of our main findings.

2. Methodology

2.1. Inclán and Tiao's (IT) (1994) ICSS algorithm

Suppose ε_t is a time series with zero mean and with unconditional variance σ^2. Suppose the variance within each interval is given by τ_j^2, where $j = 0, 1, \ldots, N_T$ and N_T is the total number of variance changes in T observations, and $1 < k_1 < k_2 < \ldots < k_{NT} < T$ are the change points.

$$\sigma_t^2 = \tau_0^2 \quad \text{for} \quad 1 < t < k_1 \tag{1a}$$

$$\sigma_t^2 = \tau_1^2 \quad \text{for} \quad k_1 < t < k_2 \tag{1b}$$

$$\sigma_t^2 = \tau_{NT}^2 \quad \text{for} \quad k_{NT} < t < T. \tag{1c}$$

In order to estimate the number of changes in variance and the time point of each variance shift, a cumulative sum of squares procedure is used. The cumulative sum of the squared observations from the start of the series to the kth point in time is given as:

$$C_k = \sum_{t=1}^{k} \varepsilon_t^2$$

where $k = 1, \ldots, T$. The D_k (IT) statistics is given as:

$$D_k = \left(\frac{C_k}{C_T}\right) - \frac{k}{T}, \quad k = 1, \ldots, T \quad \text{with} \quad D_0 = D_T = 0 \tag{2}$$

where C_T is the sum of squared residuals from the whole sample period.

If there are no sudden changes in the variance of the series then the D_k statistic oscillates around zero and when plotted against k, it looks like a horizontal line. On the other hand, if there are sudden changes in the variance of the series, then the D_k statistics values drift either above or below zero. Critical values obtained from the distribution of D_k can be used to detect the significant changes in the variance under the null hypothesis of a constant variance. The null hypothesis of constant variance is rejected if the maximum absolute value of D_k is greater than the critical value. Hence, if $\max_k \sqrt{(T/2)}|D_k|$ is more than the predetermined boundary, then k^* is taken as an estimate of the variance change point. The 95th percentile critical value for the asymptotic distribution of $\max_k \sqrt{(T/2)}|D_k|$ is 1.358 (Inclán and Tiao, 1994; Aggarwal et al., 1999) and hence the upper and the lower boundaries can be set at ± 1.358 in the D_k plot. If the value of the statistic falls outside these boundaries then a sudden change in variance is identified.

2.2. Extreme value estimator of variance (RS estimator)

Rogers and Satchell (1991) derive an extreme value estimator for the unconditional variance of an asset price which has the attractive property that it remains unbiased for any value of the drift. Suppose O_t, H_t, L_t and C_t are the opening, high, low and closing prices of an asset on day t. Define:

$$b_t = \log\left(\frac{H_t}{O_t}\right)$$
$$c_t = \log\left(\frac{L_t}{O_t}\right)$$
$$x_t = \log\left(\frac{C_t}{O_t}\right).$$

Suppose *varx* denotes the usual estimator of σ^2, i.e.

$$varx = \frac{1}{N-1}\sum_{n=1}^{N}(x_n - \hat{\mu})^2$$

where

$$\hat{\mu} = \frac{1}{N}\sum_{n=1}^{N} x_n.$$

Let $u_t = 2b_t - x_t$ and $v_t = 2c_t - x_t$, define the extreme value estimator *varux* and *varvx*:

$$varux = \frac{1}{N}\sum_{n=1}^{N}\left(\frac{u_n^2 - x_n^2}{2}\right)$$
$$varvx = \frac{1}{N}\sum_{n=1}^{N}\left(\frac{v_n^2 - x_n^2}{2}\right).$$