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Sudden changes in extreme value volatility estimator: Modeling and forecasting with economic significance analysis

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ABSTRACT

This study provides a framework based on an extension of the conditional autoregressive range (CARR) model which incorporates the impact of sudden changes in the unconditional volatility. This study proposes to use the RS estimator in the CARR model (called henceforth the CARRS model) instead of using the range. The results of the CARRS models with and without volatility breaks are compared with the results of the GARCH models with and without volatility breaks. We also compare the forecasting performance of CARRS models with the forecasting performance of EGARCH, TGARCH and FIGARCH models based on error statistics and regression approach. The findings indicate that the CARRS model with volatility breaks effectively captures the dynamics of volatility and provides better out-of-sample forecasts when compared with GARCH, EGARCH, TGARCH and FIGARCH models. We also devise a trading strategy to examine the economic significance of the proposed framework which indicates that the investor can make substantial gains (approximately 6%–10%) in return for most of cases based on volatility forecasts of CARRS model with volatility breaks. Results based on robustness check are consistent with our main findings.

1. Introduction

The analysis and prediction of volatility play a crucial role in financial markets due to its importance for investment decisions and portfolio management (Aizenman and Marion, 1999), option pricing (Hull and White, 1987), risk management (Granger, 2002) and in implementing trading strategies (Poon and Granger, 2003). Precise forecasts of volatility can help portfolio managers and investors to customize their trading strategies and to rebalance and hedge their positions to deal with the investment risks based on an anticipation of future movements of the market. In the investment literature, volatility is known to be a measure of market risk which may be adversely affected by uncertain movements in the financial markets (Holton, 2003). These uncertain movements may be due to wars, terrorist attacks, interest rate hikes, recession, change in investors' perception, crashes and crises in financial markets. Regulators, central banks and policy makers also have an interest in precise volatility prediction to effectively implement policy measures for maintaining stability in financial markets and for assessing the effectiveness of these policies depending on the required goals (Poon and Granger, 2003).

The daily unconditional volatility associated with an asset has long been estimated using daily closing prices. The widely used volatility estimators include the demeaned squared daily return and the absolute daily return. However, these estimates are noisy in nature (Alizadeh et al., 2002). An alternative approach would be to use intraday high frequency data which is generally very expensive and demanding in its computational requirements. However, the volatility estimated using high frequency data may be affected by market microstructure issues (Dacorogna et al., 2001). In addition, high frequency data is not available for many assets and sometimes may be available for smaller intervals only.

On the other hand, the literature starting with Parkinson (1980) and Garman and Klass (1980) and extended by Rogers and Satchell (1991) and Yang and Zhang (2000) has highlighted the value of using opening, high, low and closing prices of an asset for the efficient estimation of volatility. Among all these range-based volatility estimators, the RS estimator proposed by Rogers and Satchell (1991) stands out because it 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 (Kumar and Maheswaran, 2013a; Maheswaran et al, 2011). 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.

The Generalized Autoregressive Conditional Heteroskedasticity (GARCH) class of models is known to be a popular tool in modeling the dynamics of the return based volatility (Bollerslev, 1986 and Engle, 1982). The popularity of the GARCH class of models has its roots in capturing many stylized facts such as volatility clustering, in its ability to account for dynamic changes in conditional volatility over various horizons and also in providing good in-sample estimates. However, the literature provides evidence that range-based conditional

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volatility models perform much better than the conventional GARCH models. Chou (2005) proposes the Conditional Autoregressive Range Model (CARR) to capture the dynamics of range-based volatility. In particular, he finds that the CARR model can forecast the return based volatility more effectively than can the GARCH model. Brandt and Jones (2006) propose another model to capture the dynamics in range-based volatility by combining Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH) models with data on range and find that the new models effectively forecast the return-based volatility. They find that the range-based conditional volatility models can better forecast volatility over longer horizons up until 1 year in comparison to similar forecasts made by GARCH models. Li and Hong (2011) propose the range-based autoregressive volatility model and their findings are also in line with that of Chou (2005) and Brandt and Jones (2006), in that range-based conditional volatility models exhibit good performance in forecasting future volatility. This study works with a modified form of the CARR model in which instead of the range, this study proposes the use of the RS estimator and name the model as the CARRS model. In addition, this study also looks at the forecasting performance of the CARRS model under the impact of sudden changes in the unconditional volatility by explicitly incorporating volatility regimes in the model.

It is well known that the unconditional volatility in a financial market may be significantly affected by infrequent structural breaks or regime shifts due to domestic and global macroeconomic and political events (Aggarwal et al., 1999; Kumar and Maheswaran, 2012). Sudden changes in the unconditional volatility can also influence the intensity or the direction of information flow among markets, stocks or portfolios as shown by Ross (1989). A good conditional volatility model should make provisions to incorporate these structural breaks in the unconditional volatility in order to obtain better volatility forecasts. Inclán and Tiao (1994) propose the Iterated Cumulative Sum of Squares (ICSS) algorithm, referred to as IT-ICSS hereafter, to detect the sudden changes 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 detects both a significant increase and decrease in the unconditional volatility and, hence, can help in identifying both the beginning and the ending of volatility regimes. The IT-ICSS test has been extensively used in detecting sudden changes in the unconditional volatility of time series based on close-to-close returns. Aggarwal et al. (1999), Malik (2003), Fernandez and Arago (2003), Malik et al. (2005), Hammoudeh and Li (2008), Kumar and Maheswaran (2013b) and many more also highlight the fact that incorporating sudden changes in the conditional volatility model reduces the persistence of volatility. Kumar and Maheswaran (2013a) find that the IT-ICSS algorithm exhibits superior size and power properties when applied with the RS estimator in comparison to demeaned squared returns. They also find that most of the breaks detected in the RS estimator can be related to macroeconomic and political events, while very few of the breaks detected in demeaned squared returns can be related to any macroeconomic event. This study incorporates the sudden changes in the RS estimator in the CARRS model and examines the impact of such sudden changes on the persistence of conditional volatility.

Following Kumar and Maheswaran (2013a), the objective in this paper is to extend this setup to examine the impact of sudden changes in the RS estimator on the persistence of conditional volatility and to incorporate the impact of these sudden changes in a model of conditional volatility based on the RS estimator. In addition, this study looks for if it can effectively forecast volatility over different forecast horizons. For this, this study proposes the use of the Conditional Autoregressive Rogers and Satchell (CARRS) model which is similar to the Conditional Autoregressive Range (CARR) model proposed by Chou (2005) in almost all respects except that instead of using the range as an input variable to model conditional volatility, this study proposes the use of the RS estimator because it is unbiased regardless of the drift parameter. To incorporate the impact of sudden breaks in the unconditional volatility in the CARRS model, this study makes use of dummy variables in the CARRS model to represent each volatility regime. Furthermore, this study makes use of the IT-ICSS algorithm to detect sudden changes in the unconditional volatility based on demeaned square returns as well and incorporate these sudden changes in GARCH models, so that the study can compare the results based on the CARRS models with and without volatility breaks with the results from the GARCH models with and without volatility breaks. The study undertakes the analysis on S&P 500, FTSE 100, SZSE Composite, FBMKLCI and CAC 40 indices covering major developed, advanced emerging and emerging markets. This study uses CARRS-B to represent the CARRS model with volatility breaks, CARRS to represent the plain vanilla CARRS model, GARCH-B to represent the GARCH model with volatility breaks and GARCH to represent the plain vanilla GARCH model. We also compare the forecasting performance of the CARRS models with the forecasting performance of the EGARCH, the TGARCH and the FIGARCH models based on the error statistics and regression approach. The findings indicate that the CARRS model with breaks in the unconditional volatility effectively captures the dynamics of conditional volatility and provides better out-of-sample forecasts relative to the asymmetric (EGARCH and TGARCH models) and long memory (FIGARCH model) volatility models and the GARCH models with or without structural breaks in the unconditional volatility. We also devise a trading strategy that makes use of forecasted variance to earn substantial gain so as to highlight the economic significance of the proposed framework. The results based on economic significance are also in favor of the CARRS based frameworks. We also undertake robustness check based on different in-sample and out-of-sample periods for out-of-sample volatility forecast evaluation exercises. Results are still consistent with the main findings.

The remainder of this paper is organized as follows: Section 2 introduces the CARRS models with and without volatility breaks. Section 3 describes the data and discusses the computational details. Section 4 reports the empirical results and Section 5 concludes with a summary of main findings.

2. Methodology

2.1. Inclan 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 t_j^2, where $j = 0, 1, \ldots, N_T$ and N_T is the total number of variance changes in T observations, and $1 < k_1 < k_2 < \ldots < k_{N_T} < T$ are the change points.

$$\sigma_t^2 = \tau_0^2 \quad for \quad 1 < t < \kappa_1 \tag{1a}$$

$$\sigma_t^2 = \tau_1^2 \quad for \quad \kappa_1 < t < \kappa_2 \tag{1b}$$

…

$$\sigma_t^2 = \tau_{N_T}^2 \quad for \quad \kappa_{N_T} < t < T \tag{1c}$$

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:

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

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