INDIVIDUAL STOCK VOLATILITY MODELING WITH GARCH–JUMPS MODEL AUGMENTED WITH NEWS ANALYTICS DATA

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Abstract

Based on empirical evidences for some of FTSE100 companies, it will be examined two GARCH models with jumps. First we consider the well-known GARCH model with jumps proposed in [5]. Then we introduced the GARCH-Jumps model augmented with news intensity and obtained some empirical results.

1 Introduction

The work presented here tries to evaluate the impact of news on stock volatility through a small empirical study on augmented GARCH–Jumps models. While news analytics tools became more popular among investors as indicated in [6], there are not so much research works studying quantitative impact of news on stock volatility. It is worth to be mentioned the pioneering works [8] and [7]. In the paper of [8] firm-specific announcements were used as a proxy for information flows. It was shown that there exists a positive and significant impact of the arrival rate of the selected news variable on the conditional variance of stock returns on the Australian Stock Exchange in a GARCH framework. They split all their press releases into different categories according to their subject. In the second of the papers the author examines impact of news releases on *index* volatility. In the paper [9] was shown that the GARCH(1,1) model augmented with volume does remove GARCH and ARCH effects for the most of the FTSE100 companies, while the GARCH(1,1) model augmented with news intensity has difficulties in removing the impact of log return on volatility.

Based on empirical evidences for some of FTSE100 companies, in the paper it will be examined two GARCH models with jumps. First we consider the well-known GARCH model with jumps proposed in [5]. Then we introduced the GARCH-Jumps model augmented with news intensity and obtained some empirical results. The main assumption of the model is that jump intensity might change over time and that jump intensity depends linearly on the number of news. It is not clear whether news adds any value to a jump-GARCH model. However, the comparison of the values of log likelihood shows that the GARCH-Jumps model augmented with news intensity performs slightly better than "pure" GARCH or the GARCH model with Jumps.

2 Models Description

2.1 GARCH model

We recall [1] that a process (ϵ_t) is said to be the generalized autoregressive conditionally heteroscedastic or GARCH(1,1) process if $\epsilon_t = \sigma_t u_t, t \in \mathbb{Z}$, where (σ_t) is a nonnegative process such that

$$\sigma_t^2 = \omega + \alpha\epsilon_{t-1}^2 + \beta\sigma_{t-1}^2. \tag{1}$$

In the model, α reflects the influence of random deviations in the previous period on σ_t, whereas β measures the part of the realized variance in the previous period that is carried over into the current period. The sizes of the parameters α and β determine the short-run dynamics of the resulting volatility time series, i.e. the sum $\alpha + \beta$ of these parameters reflects the degree of persistence. Large ARCH error coefficients α mean that volatility reacts intensely to market movements, while large GARCH lag coefficients β indicate that shocks to volatility persist over time.

2.2 GARCH–Jumps Model Augmented with News Analytics Data

We are going to analyze the impact of news process intensity on stock volatility by extending GARCH-Jump models proposed and studied in [5].

Let X_t be the log return of a particular stock or the market portfolio from time $t-1$ to time t. Let I_{t-1} denotes the past information set containing the realized values of all relevant variables up to time $t-1$. Suppose investors know the information in I_{t-1} when they make their investment decision at time $t-1$. Then the relevant expected return μ_t to the investors is the conditional expected value of X_t, given I_{t-1}, i.e.

$$\mu_t = E(X_t | I_{t-1}).$$

The relevant expected volatility σ_t^2 to the investors is conditional variance of X_t, given I_{t-1}, i.e.

$$\sigma_t^2 = Var(X_t | I_{t-1}).$$

Then

$$\epsilon_t = X_t - \mu_t$$

is the unexpected return at time t. Following [5] we suppose that news process have two separate components: normal and unusual news,

$$\epsilon_t = \epsilon_{1,t} + \epsilon_{2,t}. \tag{2}$$

The first term in (2) reflects the impact of normal news to volatility:

$$\epsilon_{1,t} = \sigma_t u_t, t \in \mathbb{Z},$$

where (u_n) be a sequence of i.i.d. random variables such that $u_t \sim N(0,1)$, (σ_t) is a nonnegative process such that

$$\sigma_t^2 = \alpha_0 + \alpha_1\epsilon_{t-1}^2 + \beta_1\sigma_{t-1}^2$$

and $\alpha_0, \alpha_1, \beta_1 > 0$.

The second term in (2) reflects the result of unexpected events and describe jumps in volatility:

$$\epsilon_{2,t} = \sum_{k=1}^{N_t} Y_{t,k} - \theta\lambda_t,$$

where $Y_{t,k} \sim \mathcal{N}(\theta, \delta^2)$, N_t is a Poisson random variable with conditional jump intensity

$$\lambda_t = a + b\lambda_{t-1} + c\zeta_{t-1} + \rho n_{t-1},$$

where $\zeta_{t-1} = \mathbb{E}(N_{t-1}|I_{t-1}) - \theta\lambda_{t-1}$, and n_{t-1} is the number of news from $t-2$ to $t-1$ respectively. Therefore we directly take into account the qualitative data of news intensity and news sentiment score (source: RavenPack News Scores).

3 Empirical results

Our sample covers a period ranging from July 1, 2005 to December 31, 2011. Our sample is composed of the 92 UK stocks that were part of the FTSE100 index in the beginning of 2005 and which survived through the period of 6 years. We have deleted 8 stocks that have not survived.

Daily stock closing prices (the last daily transaction price of the security) are obtained from Yahoo Finance database. All news analytics data were given by Raven Pack News Analytics (RPNA). RPNA is a news sentiment analysis service that provides a look into the sentiment of more than 28,000 publicly traded companies worldwide. Each score is a weighed balance of sentiment in articles published by professional newswires (such as Dow Jones and Reuters) and hundreds of financial sites, online newspapers and even blogs.

The null hypothesis of normality is rejected for all stocks except a few stocks. The Box-Ljung Q-statistic shows that there is no autocorrelation of log returns. Using this fact, we do not include autoregressive and moving average terms in mean equation. We will assume $\mu = \mathbb{E}(r_t)$.

Consistent with the findings in [4] and [9], we find that the p-values of Shapiro-Wilk statistic of log returns for all companies are close to zero. We may conclude that all series are non-normal.

Let r_t and r_t^* denote log return of the stock and log return of FTSE100 index on interval t respectively. We will consider a process $(\epsilon_t) = r_t - (\theta_1 + \theta_2 r_t^*)$, where θ_1 and θ_2 are parameters of models.

It has been obtained

- Maximum likelihood estimates of the GARCH(1,1) model defined by (1) for log returns of closing daily prices shows that volatility persistence, i.e. $\alpha + \beta$, is more than 0.9. It provides clear evidence of GARCH effect. The coefficients of the model are highly significant.

- Maximum likelihood estimates of GARCH(1,1) model with Jumps (with constant jump intensity, i.e. it is assumed that $b = c = 0$) for log returns of the closing daily prices of the 21 companies for 6 years (July 5, 2005 - December 31, 2011).

- Maximum likelihood estimates of GARCH(1,1)–Jumps model *augmented with news intensity* for log returns of the closing daily prices for the five companies (January 5, 2005 - December 31, 2011) shows that model coefficients and ρ are significant for most of the companies.

Note that the GARCH model with jumps (the null model) is a special case of the augmented GARCH-Jumps model (the alternative model). Therefore, to compare the fit of two models it can be used a likelihood ratio test (see e.g. [3]). Results of likelihood ratio test shows that the alternative model is preferable with confidence level 5% for almost all companies .

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