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Long memory properties in return and volatility: Evidence from the Korean stock market

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Abstract

In this paper, we study the dual long memory property of the Korean stock market. For this purpose, the ARFIMA–FIGARCH model is applied to two daily Korean stock price indices (KOSPI and KOSDAQ). Our empirical results indicate that long memory dynamics in the returns and volatility can be adequately estimated by the joint ARFIMA–FIGARCH model. We also found that the assumption of a skewed Student-t distribution is better for incorporating the tendency of asymmetric leptokurtosis in a return distribution.

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Keywords: Dual long memory; ARFIMA–FIGARCH; Skewed Student-t distribution; Korean stock market

1. Introduction

Long memory dynamics are important indicators for determining non-linear dependence in the conditional mean and variance of financial time series. Unlike the knife-edge distinction between stationary process $I(0)$ of autoregressive moving average (ARMA) model and non-stationary process $I(1)$ of autoregressive integrated moving average (ARIMA) model, the fractionally integrated process $I(d)$ or ARFIMA model is characterized by the autocorrelation function which decays at a hyperbolic rate [1–3].

The prior literature on long memory in the conditional mean and variance had evolved independently, as the phenomena appear distinct [4–6]. However, long memory phenomena are often observed in both the conditional mean and variance at the same time. Based on this idea, the empirical studies have focused on the dual long memory property in the conditional mean and variance [7–9].

Many statistical approaches have identified the probability form of financial distributions [10–14]. The distributional properties of financial data returns are usually characterized by leptokurtic Lévy distribution [15,16], power-law stability [17,18], scaling law [10,12,19–25]. More recent work [26,27] has employed

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ARCH–GARCH models with the assumption of non-Gaussian distribution innovations for measuring and controlling financial risks.

The primary focus of this paper is to investigate the dual long memory property in the returns and volatility of Korean stock market using the ARFIMA–FIGARCH model. The ARFIMA–FIGARCH model can provide a useful way of analyzing the relationship between the conditional mean and conditional variance of a process exhibiting the long memory property, simultaneously. Additionally, this paper also considers the distributional properties of stock returns using the normal and skewed Student-t distributions. Because the residuals suffer from excess kurtosis and skewness, implying the assumption of normal distribution is not suitable for capturing asymmetry and tail-fatness in a return distribution.

The rest of this paper is organized as follows. Section 2 discusses the ARFIMA–FIGARCH model and estimated densities, i.e. normal and skewed Student-t distribution innovations. Section 3 provides the statistical characteristics of sample data, and the estimation results of the ARFIMA model, FIGARCH model, and the ARFIMA–FIGARCH model. The final section, Section 4, will contain some concluding remarks.

2. Model framework and estimation method

2.1. ARFIMA– FIGARCH model

Granger [1], Granger and Joyeux [2], and Hosking [3] have developed the ARFIMA model as a popular parametric approach to test the long memory property in financial time series. The idea of this model is to consider the fractionally integrated process $I(d)$ in the conditional mean. The ARFIMA(n, ξ, s) model can be expressed as a generalization of the ARIMA model as follows:

$$\Psi(L)(1-L)^{\xi}(y_t-\mu)=\Theta(L)\varepsilon_t, \tag{1}$$

$$\varepsilon_t = z_t\sigma_t, \quad z_t \sim N(0,1), \tag{2}$$

where ε_t is independent and identically distributed (i.i.d.) with a variance σ^2, and L denotes the lag operator. $\Psi(L)=1-\psi_1 L-\psi_2 L^2-\cdots-\psi_n L^n$ and $\Theta(L)=1+\theta_1 L+\theta_2 L^2+\cdots+\theta_s L^s$ are the autoregressive (AR) and moving-average (MA) polynomials with standing in outside of unit roots, respectively.

Following Hosking [3], when $-0.5<\xi<0.5$, the y_t process is stationary and invertible. For such processes, the effect of shocks to ε_t on y_t decays at the slow rate to zero. If $\xi=0$, the process is stationary, so-called short memory, and the effect of shocks to ε_t on y_t decays geometrically. For $\xi=1$, the process follows a unit root process. If $0<\xi<0.5$, then the process exhibits positive dependence between distant observations implying long memory. If $-0.5<\xi<0$, then process exhibits negative dependence between distant observations, so-called anti-persistence.

Similar research on the volatility has led to an extension of the ARFIMA representation in ε_t^2, leading to the FIGARCH model of Baillie et al. [28]. The FIGARCH (p, d, q) can be expressed as follows:

$$\phi(L)(1-L)^d\varepsilon_1^2=\omega+[1-\beta(L)]v_t, \tag{3}$$

where $\phi(L)\equiv\phi_1 L+\phi_2 L^2+\cdots+\phi_q L^q$, $\beta(L)\equiv\beta_1 L+\beta_2 L^2+\cdots+\beta_p L^p$ and $v_t\equiv\varepsilon_t^2-\sigma_t^2$. The $\{v_t\}$ process can be interpreted as the innovations for the conditional variance and has zero mean serially uncorrelated. All the root of $\phi(L)$ and $[1-\beta(L)]$ lie outside the unit root circle.

The FIGARCH model provides greater flexibility for modeling the conditional variance, as it accommodates the covariance stationary GARCH model for $d=0$ and the non-stationary IGARCH model for $d=1$. Thus, the attraction of the FIGARCH model is that, for $0<d<1$, it is sufficiently flexible to allow for intermediate range of persistence.

The estimation of the ARFIMA–FIGARCH model is done by an approximate quasi-maximum likelihood estimation method [29]. The fractional differencing operator, $(1-L)^{\xi}$, is defined by the binomial series