THE KOREAN ECONOMIC REVIEW
Volume 24, Number 2, Winter 2008

ASYMMETRY AND LONG MEMORY FEATURES IN VOLATILITY: EVIDENCE FROM KOREAN STOCK MARKET

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We investigate the asymmetry and long memory features in the volatility of the Korean stock market. For this purpose, we examine some GARCH class models that can capture these volatility stylized factors in the KOSPI 200 Index return data. From the results of estimation and diagnostic tests, we find that the decrease in volatility asymmetry in the crisis period is due to the introduction of derivatives markets (index futures and option trading) and the market liberalization, and that the degree of long memory features becomes lower after the financial crisis, implying that the financial crisis has the efficiency of the Korean stock market.

JEL Classification: C12, C32, G14
Keywords: Volatility, Asymmetry, Long Memory, FIAPARCH, Korean Stock Market

I. INTRODUCTION

A recent concern in a growing body of literature has suggested the observed asymmetric response of stock return volatility to news, i.e. stock return volatility tends to rise more following a large price fall (bad news) than following a price rise (good news) of the same magnitude, a

Received for publication: Aug. 1, 2008. Revision accepted: Dec. 15, 2008.

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phenomenon known as the leverage effect (Black, 1976; Christie, 1982; Nelson, 1991; and Campbell and Hentschel, 1992). This phenomenon leading to predict asymmetry of the conditional variance has been commonly observed in stock return volatility (Engle and Ng, 1993).

Since the empirical work of Black (1976), many studies have attempted to explain the causes of asymmetry of volatility. There are two traditional explanations for asymmetric response of volatility to news. The first explanation highlights the role of financial and operating leverage effect. For example, if the value of a leveraged firm drops, its equity will become more leveraged, causing the volatility of returns to rise because risk is positively related to firm leverage (Black, 1976). During the Korean financial crisis, the debt-to-equity ratios have increased along with the volatilities of stock returns in most listed firms. Ku (2000) empirically examined that the degree of asymmetric volatility depends on the firm's debt-to-equity ratio in the Korean stock market. However, Christie (1982) and Schwert (1989) argued that the financial leverage effect is insufficient to explain the size of the observed asymmetry in the volatility of stock returns.

The second explanation is that a volatility feedback effect brings about asymmetries on volatility (French, Schwert and Stambaugh, 1987; and Bekaert and Wu, 2000). That is, the increased volatility raises expected stock returns and lowers current stock prices, dampening volatility in the case of good news and increasing volatility in the case of bad news. As a consequence, stock return volatility is characterized by large negative returns being more common than large positive returns, and price changes are correlated with future volatility (McMillan and Speight, 2003). However, Byun, Jo and Cheong (2003) empirically tested these two explanations and found that the asymmetric volatility of the Korean stock market is not related to the volatility feedback effect, but depends on the leverage effect.

In the absence of a good empirical model for asymmetric volatility, the GARCH class models have been refined to describe the asymmetric feature in the volatility of stock returns. For example, models such as the exponential GARCH (EGARCH) process introduced by Nelson (1991), the GJR-GARCH model of Glosten, Jagannathan and Runkle (1993), and asymmetric power ARCH (APARCH) process of Ding, Granger and Engle (1993) are among the popular asymmetric GARCH models.

Although these models allow for such asymmetries, they are unable to consider the persistence of conditional variance. To join two strands of literature that had been largely separate between asymmetry and long memory issues, recent econometric studies have developed new approaches that incorporate both asymmetry and long memory in the conditional variance. Bollerslev and Mikkelsen (1996) proposed an exponential version, a fractionally integrated exponential GARCH (FIEGARCH) model. Tse (1998) also developed the fractionally integrated asymmetric power ARCH (FIAPARCH) model.

The primary focus of this paper is to investigate the long memory property with asymmetries in the volatility of Korean Stock Price Index 200 (KOSPI 200) returns. In this purpose, this paper provides two important contributions to stock volatility dynamics in the Korean stock market. First, we analyze the feature of volatility asymmetry using the GARCH, EGARCH, and GJR-GARCH models. Unlike traditional explanations for volatility asymmetry, we put forward new hypothesis that an increase in information flow leads to reduce volatility asymmetry in terms of the introduction of index futures market as well as the market liberalization in the Korean stock market. In this sense, the financial crisis in October 1997 has played a key role in the improvement of information transmission in the Korean stock market. We compare volatility asymmetry before and after the financial crisis. Second, we also examine the long memory property together with asymmetry in volatility in terms of the fractionally integrated GARCH (FIGARCH) and FIAPARCH models. In particular, we will examine whether the financial crisis helped the Korean stock market become more efficient.

The rest of this paper is organized as follows. Section 2 discusses characteristics of symmetric and asymmetric long memory volatility models. Section 3 provides the statistical characteristics of our sample data. Section 4 examines the asymmetries as well as the long memory features in the Korean stock market. Final section presents concluding remarks.

II. METHODOLOGY

2.1. Symmetric and Asymmetric Volatility Models

To analyze the feature of volatility asymmetry, we examine the GARCH, EGARCH, and GJR-GARCH models. The standard GARCH model of Bollerslev (1986) forecasts only a symmetric feature of volatility, while both GJR-GARCH and EGARCH models are able to measure the asymmetric response of volatility to news (Engle and Ng, 1993). A simple GARCH$(1,1)$ model can be expressed as follows:

$$\varepsilon_t = \sigma_t \upsilon_t, \tag{1}$$

$$\upsilon_t \sim i.i.d. \text{ with } E(\upsilon_t) = 0, \ \operatorname{var}(\upsilon_t) = 1, \text{ and} \tag{2}$$

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2, \tag{3}$$

where $\omega > 0$, $\alpha_1 \geq 0$, $\beta_1 \geq 0$, and $\alpha_1 + \beta_1 < 1$. In the GARCH$(1,1)$ model, current conditional variance σ_t^2 depends not only on the information about volatility during the previous period ($\alpha_1 \varepsilon_{t-1}^2$; ARCH effect) but also on the fitted variance from the model during the previous period ($\beta_1 \sigma_{t-1}^2$; GARCH effect). Thus, if the return is unexpectedly large in either the upward or the downward direction, then, investors will increase the forecast of the next period's variance. Namely, this model postulates the tendency for volatility clustering.

Despite the advantage for measuring volatility clustering, the GARCH model cannot capture asymmetric response of volatility to news, because a squared error term (ε_{t-1}^2) in Equation (3) has a symmetric impact on volatility irrespective of good news or bad news. Engel and Ng (1993) argued that if a negative return shock is likely to cause more volatility than a positive return shock of the same magnitude, the GARCH model underestimates the amount of volatility responding to bad news and overestimates the amount of volatility responding to positive news.

To overcome this problem, Nelson (1991) proposed the EGARCH model with a log specification form to capture the asymmetric response of volatility to news. From Equation (3), the EGARCH$(1,1)$ specification can be written as follows:

$$\log\left(\sigma_t^2\right)=\omega+\beta_1\log\left(\sigma_{t-1}^2\right)+\alpha_1\left[\frac{|\varepsilon_{t-1}|}{\sqrt{\sigma_{t-1}^2}}-\sqrt{2/\pi}\right]+\gamma\frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}}, \tag{4}$$

where ω, β_1, α_1, and γ are constant parameters. The EGARCH specification has two advantages over the GARCH specification. First, the log specification form ensures that the conditional variance function σ_t^2 is positive even if the parameters are negative. Thus, there is no need to impose non-negativity constraints on the model parameters. Second, the EGARCH model allows positive return shocks and negative return shocks to have different impact on volatility. In Equation (4), if $\gamma<0$, negative return shocks generate greater volatility changes than positive return shocks.

Glosten, Jaganathan and Runkle (1993) also proposed an asymmetric GARCH model, i.e. the GJR-GARCH model. From Equation (3), the conditional variance function of a GJR-GARCH$(1,1)$ model can be specified as follows:

$$\sigma_t^2=\omega+\alpha_1\varepsilon_{t-1}^2+\gamma\varepsilon_{t-1}^2D_{t-1}+\beta_1h_{t-1}, \tag{5}$$

where D_t equals one if ε_t is less than zero, and D_t equals zero otherwise. The GJR-GARCH structure is similar to that of the simple GARCH model. The only difference is the presence of the γD_{t-1} dummy term in the lagged squared errors (ε_{t-1}^2). This allows good news ($\varepsilon_t>0$) and bad news ($\varepsilon_t<0$) to have different impacts on the conditional variance. For example, good news has only an α_1 impact on volatility, while bad news has an $(\alpha_1+\gamma)$ impact on volatility. Thus, if $\gamma>0$, the GJR-GARCH model can capture an asymmetric effect. However, if $\gamma=0$, the GJR-GARCH model becomes the simple GARCH model.

2.2. Symmetric and Asymmetric Long Memory Models

Numerous efforts have been made to understand persistence dynamics in conditional variance. For example, Robinson (1991) first adopted the fractional differencing concept in the conditional variance so called as long memory GARCH (LMGARCH) model.[1] Since then, many researchers have proposed extensions of GARCH type of models, which identify the long memory property in the conditional variance of financial time-series data (Baillie, Bollerslev and Mikkelsen, 1996; Davidson, 2004; Giraitis et al., 2004; and Teyssière, 1998). In particular, Baillie, Bollerslev and Mikkelsen (1996) proposed the FIGARCH model with a fractionally differencing operator $(1-L)^d$ of fractionally integrated autoregressive moving average (ARFIMA) specification.[2] A FIGARCH (p,d,q) model is defined as follows:

$$\phi(L)(1-L)^d\,\varepsilon_t^2 = \omega + [1-\beta(L)]\nu_t, \tag{6}$$

where $0<d<1$, all the root of $\phi(L)$ and $[1-\beta(L)]$ lie outside the unit root circle. Equation (6) can be re-written as follows:

$$[1-\beta(L)]\sigma_t^2 = \omega + \left[\ 1-\beta(L)-\phi(L)(1-L)^d\ \right]\ \varepsilon_t^2 . \tag{7}$$

Thus, the conditional variance of ε_t is simply given by the following:

$$\sigma_t^2 = \omega\ [1-\beta(L)]^{-1} + \left\{\ 1-[1-\beta(L)]^{-1}\phi(L)(1-L)^d\ \right\}\varepsilon_t^2 \tag{8}$$

$$\equiv \omega\ [1-\beta(L)]^{-1} + \lambda(L)\ \varepsilon_t^2, \tag{9}$$

where $\lambda(L) = \lambda_1 L + \lambda_2 L^2 + \ldots$[3] For the FIGARCH$(p,d,q)$ process to

[1] The LMGARCH model is similar to the FIGARCH model of Billie, Bollerslev and Mikkelsen (1996) using some of the feature of fractional ARIMA processes. However, the FIGARCH model is much more popular in the literature on empirical applications (Conrad and Haag, 2006).

[2] Some empirical studies have sought to identify the long memory parameter in the volatility process by applying a semi-parametric estimator or ARFIMA model to squared returns and absolute returns (Granger and Ding 1996; Breidt, Crato and de Lima 1998; Bollerslev and Wright 2000; and Andreou and Ghysles 2002). However, Wright (2002) and Sibbetsen (2003, 2004) has argued that the absolute and squared returns cause large bias in the semi-parametric estimation of long memory volatility process.

[3] The FIGARCH process has impulse response weights. For large k, $\lambda_k \approx k^{d-1}$, which provides a measure of long memory process or a process that hyperbolically decays (Baillie, Bollerslev and Mikkelsen, 1996). For the FIGARCH model, λ_k will persist at the large k and then be

be well defined and the conditional variance to be positive for all t, all the coefficients in the infinite ARCH representation must be nonnegative; i.e., $\lambda_k \geq 0$ for $k = 1, 2, \ldots$ (Bollerslev and Mikkelsen, 1996). Bollerslev and Mikkelsen (1996) imposed necessary and sufficient conditions for the non-negativity of the conditional variance of FIGARCH $(1, d, 1)$ as follows:[4]

$$\beta - d \leq \phi_1 \leq \frac{2-d}{3} \quad \text{and} \quad d\left[\phi_1 - \frac{1-d}{2}\right] \leq \beta\left(\phi_1 - \beta_1 + d\right). \tag{10}$$

The FIGARCH model provides greater flexibility for modeling the conditional variance as it accommodates the covariance stationary GARCH model when $d = 0$ and the IGARCH model when $d = 1$ as special cases. For the FIGARCH model, the persistence of shocks to the conditional variance, or the degree of long memory is measured by the fractional differencing parameter d. 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 idea of fractional differencing processes has been extended to other GARCH class of models, including the FIAPARCH model of Tse (1998). The FIAPARCH model extends the APARCH model of Ding, Ganger and Engle (1993) with a fractionally integrated process in the conditional variance. From Equation (8), a FIAPARCH(p, d, q) model is specified as follows:

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eventually convergent to zero. This means that shocks to volatility decay at the slow hyperbolic rate.

[4] Conrad and Haag (2006) surveyed the inequality constraints in the FIGARCH conditional variance equation and pointed out two remarkable properties of the FIGARCH model with regard to the non-negativity restrictions: (i) even if all estimated parameters are positive, the conditional variance becomes negative; and (ii) despite the estimate parameters are negative, the conditional variance keeps the non-negativity constrictions at the almost time lags. For these points of views, both conditions do not cover these properties of the FIGARCH model. As argued by Nelson and Cao (1992), they derived the inequality constraints which are necessary and sufficient for the non-negativity of the conditional variance in the FIGARCH(p, d, q) model with $p \leq 2$. Although they provide some implications on the necessary and sufficient conditions of non-negativity, there are little statistical properties of this model in the literature.

$$\sigma_t^\delta = \omega\left[1-\beta(L)\right]^{-1} + \left\{1-\left[1-\beta(L)\right]^{-1}\phi(L)(1-L)^d\right\}\left(|\varepsilon_t|-\gamma\varepsilon_t\right)^\delta, \quad (11)$$

where $\delta > 0$, $-1 < \gamma < 1$, and $0 < d < 1$. In the FIAPARCH model, the squared residuals ε_t^2 in Equation (8) are replaced by the function $\left(|\varepsilon_t|-\gamma\varepsilon_t\right)^\delta$ to accommodate the desired feature of asymmetric long memory in the conditional variances. When $\gamma > 0$, negative shocks give rise to higher volatility than positive shocks, and vice versa. The FIAPARCH model nests the FIGARCH model when $\delta = 2$ and $\gamma = 0$. Thus, the FIAPARCH model is superior to the FIGARCH model since the former model can capture asymmetric long memory features in conditional variances (Tse, 1998).

2.3. Model Density and Estimation Method

Under the assumption of conditional Gaussian errors, the most common approach for estimating ARCH class models is to maximize a conditional likelihood function,

$$\log\left(L_{Norm}\right) = -\frac{1}{2}T\log(2\pi) - \frac{1}{2}\sum_{t=1}^{T}\left[\log\left(\sigma_t^2\right) + \frac{\varepsilon_t^2}{\sigma_t^2}\right]. \quad (12)$$

Since high frequency data in many applications are not well described by the conditional normal distribution, subsequent inference is consequently based on the Quasi Maximum Likelihood Estimation (QMLE) technique of Bollerslev and Wooldridge (1992). The QMLE estimators, say $\hat{\theta}_T$ based on T observations, are both consistent and asymptotically normally distributed,

$$T^{1/2}\left(\hat{\theta}_T - \theta_0\right) \to N\left\{\ 0, A(\theta_0)^{-1} B(\theta_0) A(\theta_0)^{-1}\right\}, \quad (13)$$

where θ_0 denotes the true parameter values and $A(\cdot)$ and $B(\cdot)$ represent the Hessian and outer product of the gradients, respectively. Bollerslev and Wooldridge (1992) showed that the QMLE estimators obtained with the normality assumption is consistent, if the conditional mean and the conditional variance are correctly specified.

III. PRELIMINARY ANALYSIS OF THE DATA

The primary data set consists of the daily spot price index of the KOSPI 200 Index for the period from January 3, 1990 to December 29, 2005. The KOSPI 200 Index is the underlying stock index for futures and option contracts traded at the Korea Exchange (KRX)-Futures market. The KOSPI 200 Index is a capitalization-weighted index that consists of 200 blue-chips stock listed on the KRX-Stock market. Its constituent shares cover approximately 70-80% of domestic market capitalization, so the KOSPI 200 Index reflects overall market performance. The base date of the KOSPI 200 Index is January 3, 1990 with a base index 100.

In order to examine the causes of asymmetric volatility in the Korean stock market, the first step is to divide the whole sample into three sub-periods as follows:

- Pre-crisis: January 3, 1990 to September 30, 1997;
- During crisis: October 1, 1997 to August 31, 1998[5]; and
- Post-crisis: September 1, 1998 to December 29, 2005.

The price and return series of KOSPI 200 Index are illustrated in Figure 1. Before the crisis, the fluctuations of index prices are rather smooth while the index prices have shown a dramatic downward due to the October 1997.[6] Interestingly, after the Asian Financial Crisis, the cycle of KOSPI 200 Index price became short and volatile. This implies that investors rely on speculative trading due to the uncertainty of economic growth.

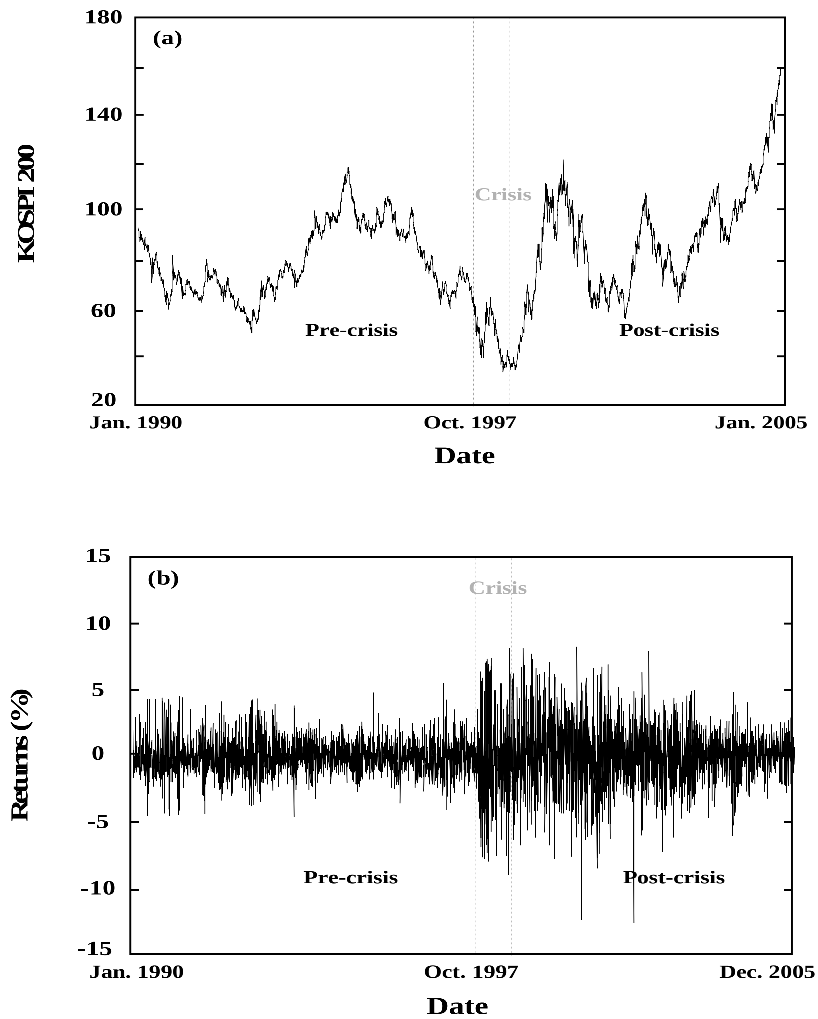
To calculate the returns, all daily price series are converted into the first logarithmic differences transformation. Figure 1(b) plots the dynamics of daily KOSPI 200 Index returns. Before October 1997, the dynamics of returns appear to be relatively, tranquil in the Korean stock market. In

[5] Park, Chung and Wang (2001) defined the financial crisis period in Korea from October 1, 1997 to September 31, 1998.

[6] From October 1 to December 27, the KOSPI 200 Index lost 37% of its value.

contrast, more large volatility which occurs in bursts has been observed in the post-crisis period. It is clear that larger stock return volatility has been observed during the economy recession (Schwert, 1990). This is asymmetric effect, where volatility tends to be higher in bear markets (Nelson, 1991). Further, although volatility has gradually decreased after the crisis, volatility has never returned to the original point in the pre-crisis period. This implies that shocks affect to volatility over long periods in the market.

[Figure 1] Dynamics of KOSPI 200 Index Prices (a) and Returns (b).



[Table 1] Descriptive Statistics for Daily KOSPI 200 Index Returns

	Whole Period	Pre-crisis Period	Crisis Period	Post-crisis Period
No. of Obs.	4,363	2,272	270	1,821
Mean (%)	0.013	-0.017	-0.237	0.089
Std. Dev. (%)	1.897	1.318	3.365	2.183
Skew.	-0.043	0.406	0.086	-0.191
Excess Kurt.	3.255	1.325	-0.057	2.396
J-B	954**	106.62**	0.358	243.12**
$Q(12)$	59.49**	45.84**	37.26**	9.960
$Q_s(12)$	1637**	817.43**	36.66**	165.85**

Notes: Under the null hypothesis for normality, the J-B (Jarque-Bera) statistic is distributed as $\chi^2(2)$. $Q(12)$ and $Q_s(12)$ are the Box-Pierce test statistics for the return series and for the squared return series at lag up to 12, respectively. ** indicates the rejection of the null hypothesis of independence at the 5% significance level.

To assess the distributional properties of the daily stock return series, the descriptive statistics of all sample periods are summarized in Table 1. The sample mean of returns is very small and indistinguishable from zero. Following the crisis, the standard deviation of the KOSPI 200 Index returns almost doubles, implying that volatility persistence typically lasts over a longer period. The KOSPI 200 Index return series reveals that they do not correspond with the normal distribution assumption except for the crisis period. The distributional statistics calculated in the table show that there are significant departures from normality as can be seen from the negative value of skewness and the large value of excess kurtosis. Likewise, the Jarque-Bera test statistics reject the null hypothesis of normality at the 5% significance level.

According to the Box-Pierce test statistics $Q(12)$, the null hypothesis of no serial correlation is rejected for all other periods apart from the post-crisis period. It indicates that there is significant evidence of serial dependence in returns for all periods excluding the post-crisis period that should be accounted for in the mean equation. This implies that the impact of non-synchronous trading on returns results in serial correlation in return series, that is, it is possible for predicting future returns from past returns. In case of the post-crisis period, the $Q(12)$ test statistic, 9.96, is not statistically significant to reject the null hypothesis. It implies that there is no correlation in the post-crisis period.

Additionally, the $Q_s(12)$ statistics to check the correlation of squared returns, 36.66~1637, suggest that there is significant evidence of serial correlation in the variance for all periods. In other words, the distribution of the next squared return, which results in volatility clustering, depends not only on the current squared return but also on several previous squared returns. Therefore, these findings such as non-normality, serial correlation, and volatility clustering characterize the dynamics of the KOSPI 200 Index returns.

To account for serial dependence in Table 1, this study considers a standard autoregressive moving average (ARMA) model for the conditional mean, assuming the standard GARCH$(1,1)$ model. Note that lag order selection issues are important when building parsimonious models for all period return series. To determine the orders n and s of the ARMA (n,s) model, this section estimates all the possible combinations for the ARMA(n,s) part with maximum n = 0, 1, 2 and s = 0, 1, 2, based on the Schwarz Bayesian Information Criteria (SIC).

[Table 2] Order Selection of the ARMA(n,s)-GARCH$(1,1)$ Model

ARMA(n,s)-GARCH$(1,1)$	Whole Period	Pre-crisis Period	Crisis Period	Post-crisis Period
$n=0, s=0$	3.802687	3.261526	5.272825	**4.241885**
$n=0, s=1$	**3.798489**	3.256791	**5.260200**	4.243944
$n=0, s=2$	3.799016	3.257285	5.278477	4.246876
$n=1, s=0$	3.799460	3.258115	5.274404	4.242281
$n=1, s=1$	3.798693	**3.254824**	5.286448	4.245870
$n=1, s=2$	3.800497	3.258116	5.292683	4.248759
$n=2, s=0$	3.799247	3.257738	5.293361	4.244380
$n=2, s=1$	3.800178	3.257335	5.312744	4.247642
$n=2, s=2$	3.801961	3.260711	5.337041	4.251767

Notes: This table provides the values of the Schwarz Bayesian Information Criterion (SIC) across the various ARMA specifications using a GARCH$(1,1)$ specification. The bold types mean the minimum value of SIC and the specification is selected in the ARMA(n,s)-GARCH$(1,1)$ models.

[Table 3] Estimation Results and Diagnostics for the KOSPI 200 Index Returns

A. Estimation Results

MA(1)-GARCH$(1,1)$

$$y_t = 0.043 + \varepsilon_t + 0.086\varepsilon_{t-1}, \qquad \sigma_t^2 = 0.031 + 0.096\varepsilon_{t-1}^2 + 0.897\sigma_{t-1}^2$$

(0.021)** (0.016)** (0.006)** (0.008)** (0.007)**

$\ln(L)$=-8263.55 Standard Deviation: 0.999

MA(1)-GJR-GARCH$(1,1)$

$$y_t = 0.007 + \varepsilon_t + 0.084\varepsilon_{t-1}, \qquad \sigma_t^2 = 0.029 + 0.059\varepsilon_{t-1}^2 + 0.072\varepsilon_{t-1}^2 D_{t-1} + 0.900\sigma_{t-1}^2$$

(0.022) (0.016)** (0.005)** (0.008)** (0.010)** (0.007)**

$\ln(L)$=-8243.79 Standard Deviation: 1.000

MA(1)-EGARCH$(1,1)$

$$y_t = 0.004 + \varepsilon_t + 0.093\varepsilon_{t-1},$$

(0.022) (0.016)**

$$\log(\sigma_t^2) = -0.137 + 0.988\log(\sigma_{t-1}^2) + 0.192\left[\frac{|\varepsilon_{t-1}|}{\sqrt{h_{t-1}}} - \sqrt{2/\pi}\right] - 0.043\frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}}$$

(0.009)** (0.002)** (0.013)** (0.006)**

$\ln(L)$=-8251.44 Standard Deviation: 1.000

B. Diagnostic Test Results

Models	GARCH$(1,1)$	GJR-GARCH$(1,1)$	EGARCH$(1,1)$
Sign Bias	-0.307	-0.418	-0.822
Positive Size Bias	-1.497	-1.034	-1.230
Negative Size Bias	0.034	0.934	0.549
Joint Test	0.880	0.727	0.747
$Q(12)$	18.30	17.44	15.97
$Q_s(12)$	14.21	14.66	18.45
SIC	3.798489	3.791352	3.794860

Sign Bias Test: $\upsilon_t^2 = a + bS_{t-1}^- + e_t$ (i)

Negative Size Bias Test: $\upsilon_t^2 = a + bS_{t-1}^-\varepsilon_{t-1} + e_t$ (ii)

Positive Size Bias Test: $\upsilon_t^2 = a + bS_{t-1}^+\varepsilon_{t-1} + e_t$ (iii)

Joint Test: $\upsilon_t^2 = a + b_1S_{t-1}^- + b_2S_{t-1}^-\varepsilon_{t-1} + b_3S_{t-1}^+\varepsilon_{t-1} + e_t$ (iv)

where υ_t is the normalized residual corresponding to the observation t for the GARCH volatility models, a and b are constant parameters, and e_t is the residual (Engle and Ng, 1993).

Notes: The values in the baskets are standard errors. The standard deviation is derived from the above models. The t-statistics for the sign bias, negative size bias and positive size bias tests are those of coefficient *b* in regressions (i), (ii), and (iii), respectively. The F-statistic is based on regression (iv). ** indicates significance at the 5% level. See Table 1.

Table 2 displays the order selection of ARMA(n,s)-GARCH$(1,1)$ models based on the values of the SIC. If a particular specification has a minimum SIC value, the specification will be selected as the best one. Thus, as shown in this table, an MA(1) specification has been retained for both the whole and crisis periods, and an ARMA$(1,1)$ specification has been chosen for the pre-crisis period, while the post-crisis period does not require including ARMA components in the conditional mean because this period return series does not show any serial correlation in Table 1.

IV. EMPIRICAL RESULTS

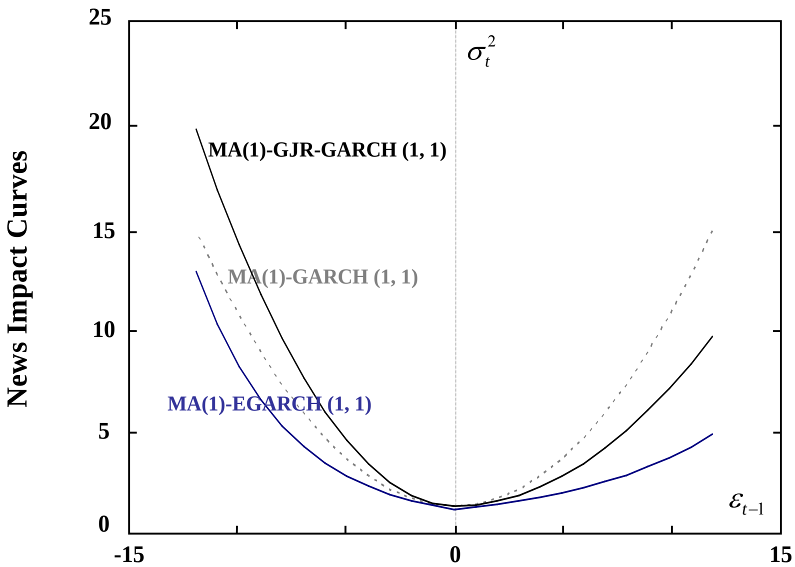
4.1. Asymmetric Features of Stock Return Volatility

To compare and demonstrate the empirical properties of the symmetric GARCH$(1,1)$ with other asymmetric models, i.e. the GJR-GARCH$(1,1)$ and EGARCH$(1,1)$ models, Table 3 reports the estimation results for the whole period. This table also includes diagnostic tests for the standard residuals from the estimated models. If the model is correctly specified, the Box-Pierce statistics $Q(12)$ and $Q_s(12)$ for the standardized residuals and squared residuals should be insignificant, implying that the residuals from estimated models are independent random processes, respectively. For checking the impact of magnitude of positive and negative unexpected returns on volatility, Engle and Ng (1993) proposed some useful diagnostic tests for GARCH class models; the sign bias test, the negative size bias test and positive bias test as well as a join test of all three. Further, the model selection criteria of SIC is provided in the last row of the table.

Beginning with the estimates of the standard MA(1)-GARCH$(1,1)$ model, the estimates of α_1 and β_1 are significantly positive and the sum of them is less than one, meaning that the estimated GARCH model is valid to express volatility clustering. On the other hand, in the MA(1)-GJR-GARCH $(1,1)$ and MA (1) -EGARCH $(1,1)$ models, asymmetric coefficients (γ) are highly significant at the 5% level, implying that an unexpected negative returns increase volatility more than an unexpected positive return of the same magnitude. In this sense, the standard GARCH model overestimates positive shocks to volatility and underestimates negative shocks to volatility.[7]

To make a clear distinction between the above three models, Table 3 calculates various diagnostic test statistics. The $Q(12)$ and $Q_s(12)$ test statistics report no evidence against independence at the 5% significance level. This implies that all estimated models are correctly specified to capture the time varying volatility. According to the diagnostic tests proposed by Engle and Ng (1993), there is no significant bias from the sign bias, positive size bias, negative size bias, or joint tests in standardized residuals of all estimated models.

[Figure 2] News Impact Curves of the Models



To assess the impact of news in the above three models, Figure 2 plots the news impact curves for the KOSPI 200 Index returns. The news impact curves can be calculated with the equations in Table 4 and shown in Figure 2. In this figure, the vertical axis represents the level of current volatility and the horizontal axis represents the lagged residuals from the

[7] The GARCH model can also exaggerate the volatility clustering. Yoon (2005) found that the GARCH model underestimates the influence of the small impact and overestimates that of the large impact.

three estimated models. While the news impact curve of MA(1)-GARCH$(1,1)$ displays a symmetric shape regardless of good or bad news, the curves of the MA(1)-GJR-GARCH$(1,1)$ and EGARCH$(1,1)$ models confirm that the good news and bad news of the same magnitude result in different impacts on the volatility of KOSPI 200 Index returns. As a result, the GJR-GARCH and EGARCH models seem to be preferable to the GARCH model in explaining the asymmetric volatility of Korean stock returns.

[Table 4] News Impact Curve Equations$(1,1)$

Model	News Impact Curves
GARCH$(1,1)$	$\sigma_t^2 = A + \alpha_1 \varepsilon_{t-1}^2$, where $A \equiv \omega + \beta_1 \sigma^2$
EGARCH$(1,1)$	$\sigma_t^2 = A\exp\left[\frac{(\gamma+\alpha_1)}{\sigma}\varepsilon_{t-1}\right]$ for $\varepsilon_{t-1} > 0$, and $\sigma_t^2 = A\exp\left[\frac{(\gamma-\alpha_1)}{\sigma}\varepsilon_{t-1}\right]$ for, $\varepsilon_{t-1} < 0$, where, $A = \sigma^{2\beta_1}\exp\left[\omega - \alpha_1\left(2/\pi\right)^{1/2}\right]$
GJR-GARCH$(1,1)$	$\sigma_t^2 = A + \alpha_1 \varepsilon_{t-1}^2$ for $\varepsilon_{t-1} > 0$, and $\sigma_t^2 = A + (\alpha_1 + \gamma)\varepsilon_{t-1}^2$ for $\varepsilon_{t-1} < 0$, where, $A \equiv \omega + \beta_1 \sigma^2$

Note: See Engle and Ng (1993) for more details.

In the meantime, it is not easy to find which model is the best one to capture volatility asymmetry in the Korean stock market. However, the SIC model selection criteria suggest that, of all three models, the MA(1)-GJR-GARCH$(1,1)$ model is the best for capturing the asymmetric volatility in the Korean stock market. This finding is consistent with that of Ku (2000) who found that the GJR-GARCH model is slightly superior to the EGARCH model in the KOSPI returns.[8]

[8] Engle and Ng (1993) argued that the EGARCH model might overestimate the forecast conditional variances in the extremely large changes of stock prices as its variability of conditional variances (β_1) is much higher than the GJR-GARCH model. However, Chang and Kim (2005) indicated that even if correctly specified, the EGARCH model has much higher value of coefficient (β_1) than that of the GJR-GARCH model in the KOSPI and KOSPI 200 returns. Oh, Lee and Lee (2000) also found that there is little difference between both estimated models. Empirically, selecting the best model might depend on the data period.

[Figure 3] Daily Conditional Variance of Returns Derived from the MA(1)-GJR-GARCH$(1,1)$ Model

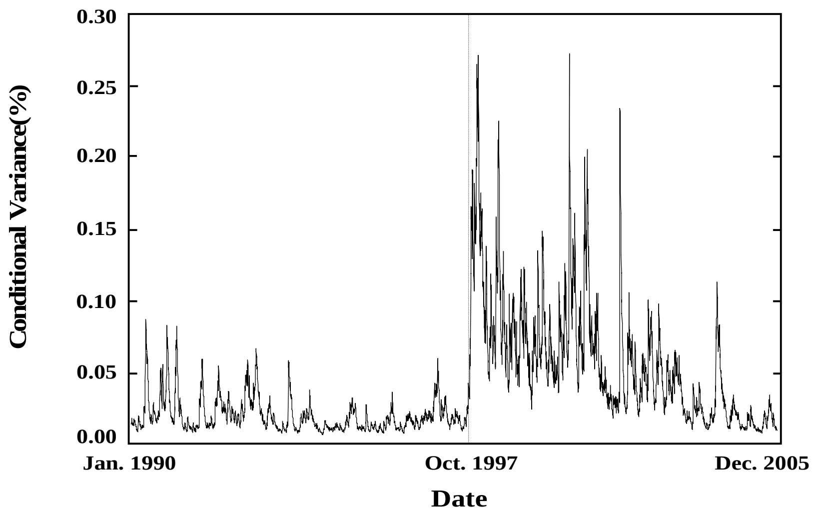


Figure 3 plots the daily conditional variance $\left(\sigma_t^2\right)$ derived from the MA(1)-GJR-GARCH$(1,1)$ model. We can find that the volatility is extremely variable, corresponding market risks. In particular, the highest peak is corresponding to the October 1997 Asian Financial Crisis, which might cause asymmetries on the volatility of stock index returns.[9] The next subsection will investigate a cause of asymmetries in the Korean stock market after and before the crisis.

4.2. Impact of Financial Crisis on the Volatility

This sub-section investigates the impact of financial crisis in the volatility asymmetry of the Korean stock market. Table 5 presents the estimation results and diagnostic tests from the ARMA-GJR-GARCH model for sub-periods of the KOSPI 200 Index returns. As shown in this table, all Box-Pierce test statistics, $Q(12)$ and $Q_s(12)$ are insignificant at the 5% level, indicating that the standardized and squared standardized residuals are i.i.d series. Thus, all estimated ARMA (n,s) -GJR-

[9] Schwert (1989) found evidence that aggregate economic series including stock returns were more volatile during the 1929-1939 Great Depression. Engle and Ng (1993) also indicated that negative returns induce more volatility than positive returns due to the 1987 stock market turmoil.

$\text{GARCH}(1,1)$ models are correctly specified to capture the dynamics of conditional mean as well as conditional variance.

[Table 5] $\text{ARMA}(n,s)$–GJR-$\text{GARCH}(1,1)$ Estimation Results for the Sub-periods

A. Estimation Results[10]			
	Pre-crisis Period	Crisis Period	Post-crisis Period
μ	-0.034 (0.026)	-0.357 (0.227)	0.112 (0.042)**
ϕ_1	-0.583 (0.116)**	-	-
θ_1	0.677 (0.105)**	0.205 (0.068)**	-
ω	0.124 (0.026)**	0.912 (0.612)	0.018 (0.008)**
α	0.107 (0.017)**	0.122 (0.080)	0.043 (0.009)**
β	0.766 (0.025)**	0.795 (0.094)**	0.940 (0.008)**
γ	0.129 (0.030)**	0.007 (0.101)	0.029 (0.010)**
$\ln(L)$	-3662.30	-696.13	-3842.60
Standard Deviation	1.000	1.000	1.004
$\alpha+\beta+0.5\gamma<1$	0.936	0.920	0.998
B. Diagnostic Test Results			
Sign Bias	-0.447	0.144	0.901
Positive Size Bias	-0.775	0.953	-0.735
Negative Size Bias	1.457	0.936	0.327
Joint Test	1.454	0.620	1.090
$Q(12)$	18.27	14.84	7.48
$Q_s(12)$	17.82	9.38	5.30

Note: ** Indicates significance at the 5%. See table 3.

Additionally, the estimated asymmetry coefficients (γ) for all sample

[10] To check the equality of estimated coefficients in the pre-crisis period (μ_1) and post-crisis period(μ_2), t-test is conducted with, $H_0:\mu_1=\mu_2$ vs $H_1:\mu_1\neq\mu_2$. The test results are in the below table.

	ω	α_1	β_1	γ
t-test Statistics	0.181	0.109	2.977**	3.175**

The t-test statistics for coefficients β_1 and γ reject the null hypothesis of equality at the 5% significance level.

periods are positive and significantly different from zero except for the crisis period. This means that unexpected negative returns (bad news) have more significant impact to the volatility of stock returns rather than unexpected positive returns (good news). However, for the crisis period, the coefficient of asymmetric volatility is insignificant due to an unusually volatile period, which might distort the estimates of the GJR-GARCH model. Hence, it appears that there is little evidence of volatility asymmetry during the crisis period.

From Table 5, we can find some interesting features on the long memory and asymmetry in the volatility of Korean stock market. First, looking at the volatility persistence between the pre-crisis and post-crisis periods, the sum of coefficients α_1 and β_1 for all sub-periods is highly significant at the 5% level, and the stationary condition of Ling and McAleer (2002) is valid for both cases. In particular, the value of in the pre-crisis period is lower than that in the post-crisis period. This implies that volatility is more persistent in the post-crisis period than in the pre-crisis period. The difference of estimated coefficients between pre- and post-crisis periods is statistically significant at the 5% level (see, footnote of Table 5). In this context, the financial crisis leads to increase the volatility persistence. However, as argued by Lamoureux and Lastrapes (1990), even if the volatility persistence increases, this may not be damaging to the market. Thus, an increase in the volatility persistence could be a result of increased information flow, which could reduce asymmetric information in the stock market.

Second, the degree of asymmetries in the pre-crisis period (0.129) is higher than that in the post-crisis period (0.029). From the footnote of Table 5, the estimated asymmetric coefficient in the pre-crisis period is statistically unequal to that in the post-crisis period. This fact indicates that the financial crisis contributes to the reduction of asymmetric volatility in the Korean stock market. In other words, the financial crisis can improve the information transmission mechanism in the Korean stock market. As a result, the decrease in asymmetric volatility after the crisis is indirectly related to the traditional explanation.

Unlike the traditional explanations for volatility asymmetry, we define new hypothesis on asymmetry in the volatility of Korean stock market: an increase in information flow leads to reduce volatility asymmetry. In the case of Korean stock market, the asymmetric volatility can be attributed to two rather unique factors. The first reason for this evidence is related to market structural changes, in particular, the derivatives market.[11] The introduction of index futures and option trading may bring more private information to traders, and allow for the high speed of information flows to the underlying spot market. Therefore, it makes the spot market more liquid and less volatile since spot prices adjust more quickly to new information. This fact can be explained by low transaction costs, available short positions, low margins, and rapid execution in futures trading (Ryoo and Smith, 2004). Thus, the introduction of index futures and option trading has stimulated positive feedback or noise traders to transfer from the KOSPI 200 Index market to the futures or options market and thus reduced asymmetric volatility in the Korean stock market.[12]

Another reason is that the financial liberalization would be devoted to reduce asymmetric information in the Korean stock market. Since October 1997, the Korean stock market has been liberalized in terms of the abolishment of foreign ownership restrictions (Choe, Kho and Stulz, 1999; and Ghysels and Seon, 2005).[13] Although foreign ownership level is not the only liberalization policy implemented in the Korean stock market, it is considered of great importance in opening up the stock market to foreign investors. The financial liberalization could result in increasing information flow and enhancing information transmission mechanism in the Korean stock market, which induce the reduction of

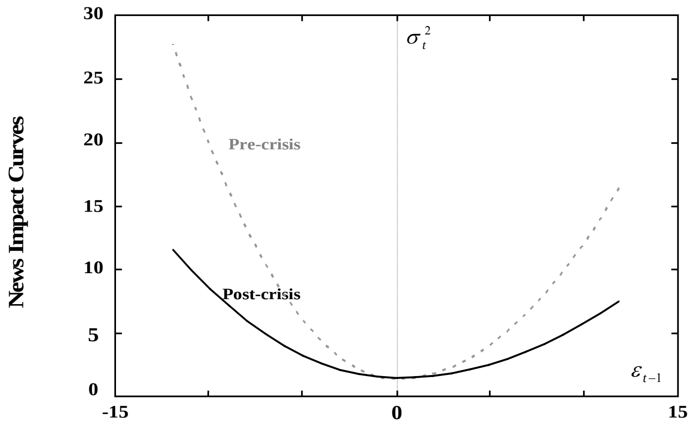
[11] The KOSPI 200 Index futures (and option contracts) was launched on May 3, 1996 (July 7, 1997).

[12] Byun and Jo (2003) and Byun, Jo and Cheong (2003) examined asymmetry on volatility before and after the introduction of KOSPI 200 index futures trading using the TGARCH and GJR-GARCH models, respectively. Their evidence indicates that the introduction of index futures trading leads to the easing of asymmetry on volatility, implying that information inefficiency is appropriate as one of the causes of the asymmetric volatility of the Korean stock market.

[13] Many studies have suggested that the liberalization date for Korean stock market is January 1999, when foreign ownership levels increased (Kim and Singal, 2000; Kassimatis, 2002). However, these studies missed a great role of October 1997 Korean financial crisis, which leads to radical financial reform in Korea. The International Monetary Fund bailout program has had a great role on reforming the Korean stock market during the crisis. Under the IMF reform program, the Korean government altered the foreign ownership ceiling three times from 26% to 55% in the two months of October and November 1997 and finally removed the restriction in May 1998 (Choe, Kho and Stulz, 1999).

asymmetric volatility and then, make the stock market more efficient.

[Figure 4] News Impact Curves for Sub-periods



The third feature on the long memory and asymmetry in the volatility of Korean stock market is following. In order to fully understand the asymmetric response of volatility to news in all periods, Figure 4 presents the news impact curves of the GJR-GARCH$(1,1)$ model. The curves appear to be the same shape in unexpected positive returns. However, in unexpected negative returns, the curve for the pre-crisis period is more asymmetric than the curves for the post-crisis period. This finding confirms that the financial crisis has reduced asymmetric volatility in terms of the improvement of information efficiency in the KOSPI 200 Index market.

4.3. Asymmetric Long Memory Features in the Volatility

The previous sections have examined the presence of asymmetric volatility using the GJR-GARCH model. Nevertheless, the GJR-GARCH specification cannot describe persistence of conditional variance. In order to circumvent the limitation, this section employs the FIGARCH model and its extension of the FIAPARCH model to capture asymmetric long memory in the volatility of KOSPI 200 Index returns. Table 6 and Table 7 provide the estimated results from the FIGARCH and FIAPARCH models in the whole, pre-, and post-crisis periods, respectively.[14]

[Table 6] Estimation Results for FIGARCH Models

Mean equation: $y_t = \mu + \rho_1 y_{t-1} + \varepsilon_t + \theta_1 \varepsilon_{t-1}$, $\varepsilon_t \mid \psi_{t-1} \sim N(0,1)$

Variance equation: $\sigma_t^2 = \omega + \beta_1 \sigma_{t-1}^2 + \left[1 - \beta_1 L - (1-\phi_1 L)(1-L)^d \right] \varepsilon_t^2$

	Whole Period	Pre-crisis Period	Post-crisis Period
Model	$\text{MA}(1)$ - $\text{FIGARCH}(1,d,1)$	$\text{ARMA}(1,1)$ - $\text{FIGARCH}(1,d,1)$	$\text{FIGARCH}(1,d,1)$
μ	0.034 (0.022)	-0.004 (0.024)	0.141 (0.040)**
ρ_1	-	-0.566 (0.118)**	-
θ_1	0.086 (0.015)**	0.667 (0.107)**	-
ω	0.100 (0.026)**	0.134 (0.037)**	0.053 (0.032)
β_1	0.364 (0.071)**	0.242 (0.127)**	0.606 (0.061)**
d	0.384 (0.037)**	0.451 (0.059)**	0.419 (0.066)**
ϕ_1	0.044 (0.049)	0.091 (0.101)	0.211 (0.042)**
$\ln(L)$	-8234.64	-3673.30	-3834.21
SIC	3.787152	3.267349	4.234042
Skewness	0.001	0.310**	-0.323**
Excess Kurtosis	1.199**	0.579**	2.067**
Jarque-Bera	261.70**	68.14**	355.74**
$Q(12)$	18.58	17.57	7.75
$Q_s(12)$	14.90	11.54	5.47
ARCH (5)	0.394	0.258	0.652

Note: ** indicates significance at the 5%. See Table 3.

From Table 6, the $\text{MA}(1)$ -$\text{FIGARCH}(1,d,1)$ model turns out to

[14] Practically, the FIGARCH and FIAPARCH models require a minimum number of observations. This minimum number is related to the truncation order of the fractional differencing operators $(1-L)^d$ for the estimated models. Beine and Laurent (2003) recommended that the truncation order of $(1-L)^d$ be set to 1,000 lags for asymptotic normality and negligible. This section rules out the crisis period to avoid the spurious results due to the lack of sample size.

capture long memory volatility for the KOSPI 200 Index returns as the long memory parameter d for all periods significantly reject the GARCH null hypothesis $(d = 0)$.[15] From this evidence, the volatility of KOSPI 200 Index returns appears to be a long memory process. Nevertheless, the FIGARCH cannot describe observed asymmetry on stock volatility. Once accounting for asymmetry in Table 7, a $\text{MA}(1)$-$\text{FIAPARCH}(1, d, 1)$ specification provides the best representation of asymmetric long memory volatility process of KOSPI 200 Index returns. In all sample periods, the coefficients of asymmetric response of volatility to news, γ, are positive and highly significant at the 5% significance level. So we can confirm that the unexpected negative returns result in more volatility than the unexpected positive returns of the same magnitude, which is in favor of the negative relationship between current returns and future volatility observed by Black (1976).

Besides, the values of long memory parameter d are statistically different from 0 and 1, indicating that the returns are long memory processes as well. As long memory exists in both the pre- and post-crisis periods, the dynamics of the long memory volatility process can be considered not to be spurious, given the structural change in the Korean stock market. More importantly, the value of long memory parameter d in the post-crisis period is lower than that in the pre-crisis period, indicating that the Korean stock market has become efficient after the financial crisis. This finding is consistent with that of Kim, Kartsaklas and Karanasos (2006), where the market liberalization improves the market efficiency of Korean stock market.

Comparing the FIGARCH model with the FIAPARCH model, the empirical results are in favour of FIAPARCH model for stock returns due to the lowest value of SIC. The serial correlation and ARCH test statistics are insignificant to reject the null hypothesis of no remaining serial correlation and ARCH effect, respectively. Thus, the estimated FIAPARCH model for the KOSPI 200 Index returns is correctly specified and fully represents the asymmetric long memory feature in the Korean

[15] Although the autoregressive parameter ϕ_1 is insignificant at the 5% level, all estimated parameters of $\text{FIGARCH}(1, d, 1)$ model fully satisfies necessary and sufficient conditions for the non-negativity of the conditional variance imposed by Bollerslev and Mikkelsen (1996).

stock market. Kang and Yoon (2006) also found similar results in the Korean stock market using the FIEGARCH model.[16]

[Table 7] Estimation Results for FIAPARCH Model

Mean equation: $y_t = \mu + \rho_1 y_{t-1} + \varepsilon_t + \theta_1 \varepsilon_{t-1}$, $\varepsilon_t \mid \psi_{t-1} \sim N(0,1)$

Variance equation: $\sigma_t^{\delta} = \omega + \left[1 - (1-\beta_1 L)^{-1}(1-\phi_1 L)(1-L)^d \right] (|\varepsilon_t| - \gamma\varepsilon_t)^{\delta}$

	Whole Period	Pre-crisis Period	Post-crisis Period
Model	MA(1)-FIAPARCH$(1,d,1)$	ARMA$(1,1)$-FIAPARCH$(1,d,1)$	FIAPARCH$(1,d,1)$
μ	0.001 (0.022)	-0.041 (0.026)	0.120 (0.041)**
ρ_1	-	-0.531 (0.125)**	-
θ_1	0.086 (0.015)**	0.632 (0.115)**	-
ω	0.073 (0.034)**	0.186 (0.039)**	-0.247 (0.152)
β_1	0.300 (0.084)**	0.343 (0.071)**	0.408 (0.112)**
d	0.351 (0.035)**	0.511 (0.063)**	0.250 (0.060)**
ϕ_1	0.007 (0.063)	0.068 (0.070)	0.181 (0.074)**
γ	0.228 (0.032)**	0.223 (0.045)**	0.117 (0.050)**
δ	2.041 (0.071)**	1.435 (0.208)**	2.414 (0.158)**
$\ln(L)$	-8234.64	-3655.97	-3828.09
SIC	3.787152	3.226202	4.235561
Skewness	0.001	0.298**	-0.321**
Excess Kurtosis	1.199**	0.462**	1.910**
Jarque-Bera	261.70**	53.90**	307.91**
$Q(12)$	18.58	18.26	7.339
$Q_s(12)$	14.90	12.41	4.930
ARCH (5)	0.394	0.313	0.523

Note: ** indicates significance at the 5%. See Table 3.

[16] Kang and Yoon (2006) do not consider a possible structural change corresponding to the October 1997 crisis in the market. In addition, Conrad and Haag (2006) argued that the FIEGARCH model exaggerates the estimates of the long memory parameter d compared with those of the FIGARCH or FIAPARCH model.

V. CONCLUSION

The asymmetry and persistence are often observed in the conditional variances of stock returns. The former contributions have dealt with long memory and asymmetry in volatility separately. This study extends the former contributions with joining two topics, long memory and asymmetry in the volatility. In this perspective, this article provides two important conclusions.

First, the GJR-GARCH model outperforms the GARCH and EGARCH models to capture an asymmetric feature in the volatility of KOSPI 200 Index returns. Furthermore, the observed asymmetric feature has been reduced since the October 1997 financial crisis. There are two unique factors for evidence of asymmetry volatility in the Korean stock market. First, the introduction of derivatives market results in the reduction of the asymmetry information from the pre-crisis period to the post-crisis period. The introduction of index futures and option trading may bring more private information to traders, and allow for the high speed of information flows to the underlying spot market. Second, the Korean stock market has become liberalized to foreign investors, which leads to increase cash inflows and enhance information transmission mechanism in the Korean stock market.

Second, to capture the asymmetry long memory feature in the volatility of stock returns, we compare the FIGARCH and FIAPARCH models. Both models fully represent the long memory volatility. However, the FIGARCH model cannot express the asymmetric volatility. Thus, we estimated the FIAPARCH model to account for asymmetry along with long memory in volatility. Analogue to the estimation results of the asymmetric coefficient γ, the value of long memory parameter d becomes lower from the pre-crisis period to the post-crisis period, implying that the financial crisis has inproved the efficiency of the Korean stock market.

Consequently, our study found asymmetry and long memory in the volatility of Korean stock market when accounting for structural changes in the market. Nevertheless, there are two limitations to the findings of this study. First, imposing regime shifts, corresponding to the October 1997 crisis does not completely solve the issue on structural breaks vs.

long memory in the volatility of stock returns. Second, Monte Carlo simulation or out-of -sample forecasting test might improve the robustness of our analysis. Following Andreou and Ghysles (2002), future research will directly incorporate infrequent break dates into volatility models and attempt to test the Monte Carlo simulation.

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