The Impact of Index Futures Trading on the KOSPI 200 Index Volatility: An Analysis of Asymmetric Volatility in the Korean Stock Market

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Abstract

This article investigates the impact of index futures trading on the KOSPI 200 index volatility in terms of an analysis of asymmetric volatility in the Korean stock market. Recently, a growing body of literature has suggested that information inefficiency is one of the causes of the asymmetric response of volatility to news. If information inefficiency is accused of the asymmetric volatility, the introduction of index futures trading will be devoted to improve information inefficiency in the underlying spot market. Due to low transaction costs, available short positions, low margins and rapid execution in futures trading, new information is transmitted to futures prices more quickly and affects spot prices through arbitrage trading. Also, the merit of index futures trading may attract noise traders away from the spot market to the futures market.

We found that the introduction of index futures trading has dramatically reduced the degree of asymmetric volatility in the post-futures period. It is clear that the introduction of index futures trading has stimulated noise and feedback traders to transfer from the spot market to the futures market and then has led to an improvement in the mechanism of information transmission in the underlying spot market. This finding is not consistent with the traditional explanations which the financial leverage and volatility feedback effects may be accused of the asymmetric response of volatility to news.

Keywords: Index futures trading; Asymmetric volatility; KOSPI 200; EGARCH model; Generalised error distribution

JEL Classifications: C22, C52, G14

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1. INTRODUCTION

The advent and explosive growth of equity index futures trading is perceived as one of the most successful innovations in financial markets. One of the important roles attributed to stock index futures trading is a mechanism for managing stock price risks. Despite contributions for stock market volatility, there has been an ongoing debate on the impact of stock index futures trading on the underlying spot market since the stock market crash of October 1987. Form an empirical perceptive, the effects whether futures index trading is desirable or undesirable on the underlying spot market have been studied with inclusive results.[1] Critics of stock index futures trading have argued that speculative trading activities result in higher volatility (Harris, 1989; Antoniou and Holmes, 1995). It is argued that the existence of trading in index futures is responsible for causing destabilisation in the underlying spot market. The alleged destabilisation could lead to an increase in uncertainty in the spot markets such as undesirable bubbles. This implication provides further regulation and supervision the derivatives industry to curb the effects of speculative trading.

On the other hand, some authors have suggested that the introduction of index futures trading may lead to lower volatility on the underlying spot market (Ross, 1989; Edwards, 1988; Ryoo and Smith, 2004). In fact, the introduction of index futures trading may bring more private information to traders, allow for the high speed of information flows to the underlying spot market, and therefore make 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

[1] See Mayhew (1999) for a comprehensive survey.

(Ryoo and Smith, 2004). Thus, the introduction of index futures trading may be devoted to make the spot market more efficient.

For understanding the impact of index futures trading on spot price volatility, many empirical studies have widely analysed the developed markets and focused on comparing spot price volatility in periods before and after the introduction of futures markets (Edwards, 1988; Kamara, Miler and Siegel, 1992; Antoniou and Holmes, 1995; Antoniou, Holmes and Priestley, 1998). One of the primary concerns of previous literature is that the introduction of index futures trading stabilises or destabilises its underlying market. Although some studies find increased volatility in developed markets, the results of empirical evidence are mixed (Mayhew, 2000).

In contrast to developed markets, a few studies deal with the impact of futures trading in emerging markets because the creation of index futures trading is a relatively recent phenomenon in these markets (Lee and Ohk, 1992; Gulen and Mayhew, 2000). It is believed that emerging markets are relatively less efficient due to lack of information efficiency. However, the introduction of index futures trading might have been devoted to perform an informational role to emerging markets. The opening of futures markets gives a rise to an opportunity to forecasting new information. If new information incorporates into the futures markets before the spot markets, the index futures trading increase the quantity of information available in the stock prices then it could be accompanied with a decrease in the volatility of the emerging markets. For example, Gulen and Mayhew (2000) examined the effect of introducing index futures trading on stock market volatility in 31 countries. They found that for the two largest markets, the USA and Japan return volatility has increased following index futures trading. However, for other emerging markets including the Korean market, they found either no significant effect or a volatility dampening effect. Thus, the introduction of index futures trading might improve information flows in the emerging stock markets.

This paper considers the Korea Stock Price Index 200 (KOSPI 200) transacted on the Korean Exchange (KRX). Although the KOSPI 200 futures contract was not launched until 3 May 1996, it is one of the fastest growing futures markets in the world's financial markets. Since the introduction of the KOSPI 200 index futures, trading has grown remarkably: an average daily trading volume was 168,737 contracts (value 14,339,198 million Korean wons) by the end of 2005.[2] The objective of this paper is to examine the impact of KOSPI 200 index futures trading on the Korean stock market. Prior literature has pursued to only test changes on market volatility and has not considered whether futures trading reduced the asymmetric response of volatility to news (Lee and Ohk 1992, Antoniou and Holmes 1995 and Ryoo and Smith 2004). Such a restricted testing framework may lead to inappropriate market policy responses to futures markets. Even if spot market volatility has increased following futures trading, this is not necessarily an undesirable consequence of futures trading because the spot market dynamics may be changed by inducing symmetric information and improving the transmission mechanism for news.

In contrast to previous literature view, our study focuses on the asymmetric response of volatility to news. Recent growing literature has suggested that the introduction of stock index futures trading may change the role of market dynamics in terms of the way in which volatility is transmitted. Cox (1976) and Merton (1995) suggested that stock index futures trading increases the amount of information and enhances the dissemination of new information to spot stock prices. This phenomenon improves the information efficiency of the spot market and induces symmetric information. Antoniou, Holmes and Priestley (1998)

[2] Source from the Korean Exchange (www.krw.co.kr).

argued that market dynamics related to the transmission of news may be responsible for asymmetries on market volatility. It is necessary to take account of testing possible the asymmetric response of volatility to news over the pre- and post-futures periods. Thus, examining the impact of index futures trading on stock market volatility allows for consideration of the asymmetric response of volatility to news provides important a guidance on the appropriate regulatory regime for futures markets.

The rest of the paper is organised as follows. Section 2 reviews a theoretical background and literature review with regard to the asymmetric response of volatility to news. Section 3 provides descriptive statistics of the sample data. Section 4 presents characteristics of EGARCH model (Nelson, 1991) which is extended with a generalised error distribution and its diagnostic tests (Engle and Ng, 1993). Section 5 discusses the empirical results. Section 6 concludes.

2. THEORETICAL BACKGROUND AND LITERATURE REVIEWS

Recently, many empirical studies have discovered an ‘asymmetric effect’ or ‘leverage effect’ that 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 (Black, 1976; Christie, 1982; Nelson, 1991). This phenomenon leading to predict asymmetry of the conditional variance has been commonly observed in stock return volatility.

Since the empirical work of Black (1976), many empirical studies have attempted to explain the causes of asymmetries on volatility. There are two main explanations for asymmetric response of volatility to news. The first explanation for the asymmetric response of volatility to news highlights the role of financial and operating leverage. For example, if the value of a leveraged firm drops, its equity will become more leveraged, causing the volatility on equity's rate of return to rise because risk is positively related to firm leverage (Christie 1982; Schwert, 1989). The second explanation is that a volatility feedback effect brings about asymmetries on volatility (French, Schwert and Stambaugh, 1987; 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 characterised by large negative returns being more common than large positive returns, and price changes are correlated with future volatility (McMillan and Speight, 2003).

Some authors including Braun, Nelson and Sunier (1991) argued that these traditional views are not sufficient to explain the extent of observed asymmetries on stock return volatility. More recent empirical studies have suggested that the asymmetric response of volatility to news is caused by information inefficiency. In the contrast to the assumption of the efficient market hypothesis, all investors are not always rational when making their decisions, their actions are not fully justified in terms of fundamental information, and therefore their actions may lead to asymmetries (Sheleifer and Summers, 1990). These traders are regarded as 'noise traders' or 'uninformed investors' since their trading strategies are based on noise and not on information (Black, 1986). Furthermore, such noise traders are likely to seek popular models that can be related to market fundamentals, but there is an element of overreaction to news (Shiller, 1984). Sheleifer and Summers (1990) also suggested investors tend to chase trends based on positive feedback strategies. For example, trend chasers buy stocks after they rise and sell stocks after they fall, and therefore they may well overact to news. When some investors follow positive feedback strategies, 'it need no longer be optimal for arbitrageurs to counter shifts in the demand of these investors' (Shleifer and Summers, 1990, p. 28). Thus, the actions of noise traders and positive feedback traders may distort stock volatility and be in direct contrast to arbitrage trading.

Some studies have documented the role of these traders and the potential effect of their actions on volatility. Kyle (1985) demonstrated that a model of insider trading is used to examine the transmission of private information from insiders to noise traders and market makers. Kyle concluded that informational asymmetries may take time be eliminated as the insider information is gradually disseminated into prices by the end of trading, so accounting for volatility clustering. Although Kyle's model provides an explanation of volatility clustering, this model is not able to explain the asymmetric response of volatility to news. Sentana and Wadhwani (1992) investigated the asymmetric response of volatility to news with a model of positive feedback traders possessing less information than their informed counterparts. They found that the extent of positive feedback trading is greater following prices falls than it is after price rises. This asymmetry is derived from positive feedback traders who tend to response to bad news (price falls) lead to greater volatility than response to good news (price rises). Thus, the actions of positive feedback traders are caused by the information inefficiency and then offering an alternative explanation for the asymmetric response of volatility to news.

If information inefficiency is one of the causes of the asymmetric volatility, the introduction of futures trading would be devoted to improve asymmetric information in the underlying spot market. In particular, futures markets have the advantages of highly liquid markets, low transaction costs, easily available short positions, low margins and rapid execution. These advantages may well bring more private information, attract additional traders, induce symmetric information and improves the mechanism of information transmission. Thus, the introduction of index futures trading has stimulated noise and feedback traders to be attracted away from the spot market to the futures market, and then asymmetries that are observed in the spot market will be reduced following the introduction of index futures trading.

Recent growing studies have suggested that the asymmetric response of volatility to news is due to information inefficiency. Merton (1995) suggested that futures trading can improve market information efficiency by reducing the asymmetric response of volatility to news. Subramanyam (1991) and Gorton and Pennacchi (1993) attempted to explain the impact of futures trading on spot market volatility in terms of considering asymmetric information. Since index futures trading regarded as 'baskets of securities' contains much lower asymmetric information than spot index trading, it seems that uninformed traders transfer from the spot markets to the futures markets. Therefore, the information efficiency may be improved by the introduction of index futures trading. Antoniou, Holmes and Priestley (1998) argued that index futures trading may change the role of market dynamics in terms of the way in which volatility is transmitted and therefore how information is incorporated into prices. They examined the impact of futures on 6 major stock markets in terms of the issue of volatility, asymmetries and market dynamics. Their evidence suggests that the introduction of index futures trading reduces asymmetric response of volatility to news, indicating that it changes market dynamics. Additionally, their result is not consistent with traditional explanations for asymmetries on volatility.

To fully understand the impact of index futures trading on the underlying spot market volatility, it is necessary to take account of the asymmetric response of volatility to news before and after futures trading. In addition, accounting for the asymmetric response of volatility to news may provide an insight into the causes of volatility asymmetries in stock markets. If there are asymmetries in the spot market pre-futures period, and then they are either eliminated or thrived on the spot market volatility once futures trading commences. This indicates that the traditional explanations, such as the financial leverage and volatility feedback effects, would not be desirable to account for volatility asymmetries in stock markets. Therefore, our conclusions will reveal the new hypothesis of observed asymmetries on stock volatility.

3. DATA AND THE DESCRIPTIVE STATISTICS

This paper considers 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 traded futures and option contracts on the KRX-Futures market. The KOSPI 200 index is a capitalisation-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 capitalisation 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. The data is obtained by the KisValue.com.[3]

The daily KOSPI 200 index prices are displayed in Figure 1. A solid line represents the introduction date of futures market and divides an entire period into two periods such as pre-future and post-future periods. Since the introduction of futures market, the KOSPI 200 index prices show a dramatic downward trend, due to the October 1997 financial crisis in Korea, and then the early 2000 IT dot.com bubble. All daily price series are converted into the first logarithmic differences (returns) of the index,

[3] http://www.kisvalue.co.kr.

$$y_t = \ln\left(P_t / P_{t-1} \right), \qquad (1)$$

where y_t is the returns for the KOSPI 200 index at time t, and P_t is the current price and P_{t-1} is the previous day's price. Figure 2 plots the daily KOSPI 200 index returns over periods from January 3, 1990 to December 29, 2005. In the pre-futures trading period, relatively small positive and negative returns appear to be tranquil in the Korean stock market. In contrast, more large volatility which occurs in bursts has been observed in the post-futures period. There are two possible reasons to large volatility clustering in this sample period. First, the introduction of index futures trading increases information flows, causing an increase in stock return volatility. Second, the current shock, the October 1997 Korean financial crisis, results in higher volatility. It is clear that larger stock return volatility has been observed during the economy recession (Schwert 1990).

In order to examine the impact of the index futures trading on stock price volatility, the first step is to divide daily prices into four groups: January 3, 1990 through December 29, 2005 (the whole sample period with 4362 observations), January 3, 1990 through May 2, 1996 (the pre-futures sample period with 1858 observations) and May 3, 1996 through December 29, 2005 (the post-futures sample period with 2504 observations). Additionally, the post-futures period include the Korean financial market crisis, an unusually volatile period.[4] To remove the effects of this unusual period, we remove the period from May 3, 1996 to September 30, 1988 from the post-futures period. This period is defined as the post-futures* period with 1794 observations.

Table 1 provides descriptive statistics for daily KOSPI 200 index returns for the whole, pre-futures, post-futures and post-futures* periods. The average daily returns for all sample

[4] Park, Chung and Wang (2001) defined the financial crisis period in Korea from October 1, 1997 to September 30, 1998.

periods are positive, but for the post-futures* period, the average returns much higher than these for other periods. Following the introduction of index futures trading, the standard deviation of returns more than doubles. Additionally, the skewness and kurtosis statistics of the returns are computed in the third and fourth rows of Table 1.[5] In the case of skewness statistics, the distributions of the whole, post-futures and post futures periods are negatively skewed, while the distribution of the pre-futures period is positively skewed. In the case of kurtosis statistics, kurtosis for all period returns is highly greater than that of the normal distribution. Such skewness and kurtosis are common characteristics in return distribution, which appear to be leptokurtoic. The Jarque-Bera test statistics indicate that the null hypothesis of normality should be rejected at the 5 % level. Thus, all sample period returns are extremely abnormal.

According to the Ljung-Box $Q(n)$ test statistics in Table 1, all period return levels reject the null hypothesis of no serial correlation expect for the post-futures* period. It indicates that there is significant evidence of serial dependence for all period returns excluding the post-futures* 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 the case of the post-futures* period, the $Q(12)$ test statistic is not statistically significant to reject the null hypothesis. It implies that there is no correlation in the post-futures* period returns.

Additionally, the $Q_s(n)$ statistics for all period squared returns suggest there is significant evidence of serial correlation in the variance. In other words, the distribution of the next squared return series depends on not only on the current squared return series but also on

[5] Skewness measures the extent to which a distribution is not symmetric about its mean value and kurtosis measures how fat the tails of the distribution are. For a normal distribution, skewness and kurtosis coefficient are zero and 3, respectively.

several previous squared returns, which results in volatility clustering. Therefore, these results imply that there are non-normality, serial correlation and volatility clustering in all sample period returns for the KOSPI 200 index. Such findings are common characteristics of stock return series. Ryoo and Smith (2004) also reported a similar disparity in findings for the daily KOSPI 200 index returns.

4. METHODOLOGY

4.1 Characteristics of the EGARCH model

To analyse the impact of futures trading on market volatility in the underlying spot market, we use the EGARCH model proposed by Nelson (1991), which allows for asymmetric response of volatility to news. Before presenting an EGARCH specification, we review how this model arises in terms of a simple GARCH specification proposed by Bollerslev (1986). A simple GARCH (1.1) model is expressed as

$$\varepsilon_t = \sqrt{h_t}\,\upsilon_t\,, \qquad (2)$$

$$\upsilon_t \sim i.i.d. \text{ with } E(\upsilon_t) = 0,\ \text{var}(\upsilon_t) = 1, \qquad (3)$$

$$h_t = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1}, \qquad (4)$$

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 h_t depends upon not only information about volatility during previous period $(\alpha_1 \varepsilon_{t-1}^2)$ but also the fitted variance from the model during the previous period $(\beta_1 h_{t-1})$. For example, investors estimate the forecasted variance from last period (the GARCH term β_1), and information about volatility observed in the previous period (the ARCH term α_1).

Thus, if the financial return series is unexpectedly large in either the upward or the downward direction, then investors will increase the estimate of next period's variance. This model postulates the tendency for volatility clustering.

Despite the advantage for measuring volatility clustering, the GARCH model can not capture asymmetric response of volatility to news because a squared error term $\left(\varepsilon_{t-1}^2\right)$ in Equation (4) has a symmetric impact on volatility irrespective of good news and 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 following bad news and overestimates the amount of volatility, responding to following positive news.

To account for this problem, Nelson extended the GARCH model with a log specification form. From Equation (2) the EGARCH $(1,1)$ specification can be re-written:

$$\log(h_t) = \omega + \beta \log(h_{t-1}) + \alpha\left[\left|\upsilon_t\right| - E\left|\upsilon_t\right|\right] + \gamma \upsilon_t , \tag{5}$$

with $\upsilon_t = \varepsilon_t / \sqrt{h_t}$,

$$\log(h_t) = \omega + \beta \log(h_{t-1}) + \alpha\left[\frac{\left|\varepsilon_{t-1}\right|}{\sqrt{h_{t-1}}} - E\left|\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}\right|\right] + \gamma \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} , \tag{6}$$

where ω , β , γ and α are constant parameters. The EGARCH specification has two advantages over the GARCH specification. First, the log specification form ensures that the conditional variance function h_t 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 differing impact on volatility (Engle and Ng, 1993). The coefficient γ measures an asymmetric impact on the conditional variance. For example, in the case of $\gamma = 0$, positive return shocks has the same effect on volatility as negative return shocks of the same amount (Gokcan, 2000). However, for $\gamma > 0$, positive return shocks will have greater impact on volatility than negative return shocks, while for $\gamma < 0$, negative return shock generate greater volatility changes than positive return shocks. Thus, the latter case supports that the Black (1976) and among subsequent studies found the effect of the asymmetries on volatility.

The EGARCH model can be estimated by maximum likelihood by specifying the density of υ_t. Almost all applications employ conditionally Gaussian errors owing to its computational ease and intuitive interpretation. For example, if ε_t is assumed to be a conditionally normal distribution, then $E|\upsilon_t| = \sqrt{2/\pi}$ in Equation (5). However, the normalised residuals obtained from ARCH class models that assume normality often are violated, and therefore given standard t-tests are unreliable. To overcome this problem, distributions with fatter tails such as a Student's-t distribution or a generalised error distribution (GED) have been suggested. This paper considers the GED originally proposed by Nelson (1991). The density of a GED random normalised variable having zero mean and unit variance is given by:

$$f(\upsilon_t) = \frac{\nu \exp\left(-0.5\left|\upsilon_t / \lambda\right|^{\nu}\right)}{\lambda 2^{(\nu+1)/\nu}\,\Gamma(1/\nu)}, \tag{7}$$

where $\Gamma(1/\nu)$ is the gamma function and λ is a constant given by

$$\lambda = \left(\frac{2^{-2/\nu}\,\Gamma(1/\nu)}{\Gamma(3/\nu)}\right)^{1/2}, \tag{8}$$

and ν is a tail-thickness parameter. Comparing to the normal distribution, the parameter ν controls the shape of the distribution allowing the GED to nest several other densities. For example, when $\nu = 2$, Equations (7) and (8) reduce the normal distribution. For $\nu < 2$, the distribution of υ_t is leptokurtic (fatter tails than the normal distribution) while for $\nu > 2$ the distribution is platykurtic (thinner tails than the normal distribution). Additionally, for $\nu = 1$, υ_t has a double exponential distribution and for $\nu = \infty$, υ_t is uniformly distributed on the interval $\left[-\sqrt{3}, \sqrt{3}\right]$ (Nelson, 1991).

4.2 Diagnostic Tests

A variety of diagnostic tests are used to determine whether various aspects of the EGARCH model are correctly. First, the skewness and excess kurtosis of the normalised residuals are displayed to determine whether the estimated models are correctly specified. Properly specified EGARCH models should be able to significantly reduce the skewness and excess kurtosis observed in the normalised residuals.

Second, Ljung-Box Q-statistics for serial correlation are performed to determine whether the normalised residuals and squared normalised residuals from the estimated models are independent and identically distributed. There is one Q-statistic for each lag k, and it is distributed as $\chi^2(k)$ under the null hypothesis of no serial correlation up to lag k. If the variance equation is correctly specified, then all Q-statistics should be statistically insignificant.

Third, Engle and Ng (1993) proposed three new diagnostic tests for GARCH class models; the sign bias test, the negative size bias test and the positive size bias test as well as a joint test of all three. They suggested that the optimal forms of the regression for conducting these tests are as followings:

$$\upsilon_t^2 = a + bS_{t-1}^{-} + \beta' z_{ot}^{*} + e_t , \qquad (9)$$

$$\upsilon_t^2 = a + bS_{t-1}^{-}\varepsilon_{t-1} + \beta' z_{ot}^{*} + e_t , \qquad (10)$$

$$\upsilon_t^2 = a + bS_{t-1}^{+}\varepsilon_{t-1} + \beta' z_{ot}^{*} + e_t , \qquad (11)$$

where υ_t is the normalised residual corresponding the observation t for GARCH volatility models, a and b are constant parameters, β is a constant parameter vector and e_t is the residual. In the sign bias test, the squared normalised residuals are regressed on a constant and a dummy variable S_{t-1}^{-} that takes a value of one, if ε_{t-1} is negative and zero otherwise in Equation (9). The sign bias test statistic is the t-statistic for the coefficient b on S_{t-1}^{-}. This test shows whether positive and negative innovations affect future volatility differently from the prediction of the model. In the negative size bias test, the squared normalised residuals are regressed on a constant and $S_{t-1}^{-}\varepsilon_{t-1}$ in Equation (10). The negative size bias test statistic is the t-statistic for the coefficient b on $S_{t-1}^{-}\varepsilon_{t-1}$. This test shows whether larger negative innovations are correlated with larger biases in predicted volatility. In the positive size bias test, the squared normalised residuals are regressed on a constant and $S_{t-1}^{+}\varepsilon_{t-1}$, where S_{t-1}^{+} is defined as one minus S_{t-1}^{-} in Equation (11). The positive size bias test statistic is the t-statistic for the coefficient b on $S_{t-1}^{+}\varepsilon_{t-1}$. The test shows whether large positive innovations are correlated with lager biases in predictable volatility. Finally, to conduct these tests jointly, the joint test of regression is given by

$$\upsilon_t^2 = a + b_1 S_{t-1}^{-} + b_2 S_{t-1}^{-}\varepsilon_{t-1} + b_3 S_{t-1}^{+}\varepsilon_{t-1} + \beta' z_{ot}^{*} + e_t , \qquad (12)$$

where a, b_1, b_2 and b_3 are constant coefficients. The t-test statistics for b_1, b_2 and b_3 are corresponding to the sign bias, the negative size bias, and positive size bias test statistics, respectively.[6] The joint test statistic is based on the Lagrange Multiplier (LM) test statistic

[6] The null hypothesis of the Joint test is $b_1 = b_2 = b_3 = 0$.

that is equal to T times R-squared from this regression (Equation (12)). The LM test statistic follows a chi-squared distribution with three degrees of freedom.

5. EMPIRICAL RESULTS

The impact of index futures trading on price volatility in the spot market is examined with the EGARCH$(1,1)$ model based on both the normal and generalised errors distributions. To account for serial dependence for all period return series found in Table 1, we consider 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, we estimate 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 (SBIC).[7] Table 2 displays the order selection of ARMA(n,s)-GARCH$(1,1)$ models based on the values of the SBIC. As shown in Table 2, an ARMA$(1,1)$ specification has been retained for both the whole and pre-futures periods, an MA(1) specification has been chosen for the post-futures period, while the post-futures* period does not require to include ARMA components in the conditional mean since this period return series does show any serial correlation in Table 1.

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[7] $SBIC = -2\frac{\log L}{T} + \frac{(k \log T)}{T}$, where $\log L$ is a log likelihood value, T is the number of observations and k is the number of estimated parameters.

All empirical $\text{ARMA}(n,s)$-$\text{GARCH}(1,1)$ models are based on the Brendt, Hall, Hall, and Hausman (BHHH) algorithm for obtaining maximum likelihood estimates. All parameter of various $\text{ARMA}(n,s)$-$\text{EGARCH}(1,1)$ models based on both the normal and generalised errors distributions are estimated in Table 3. As shown in Table 3, except for the post-futures* period, all the estimated coefficients in various ARMA models are significantly unequal to zero, indicating that all mean specifications well fit the KOSPI 200 index returns.

The results of the estimated models reveal several interesting results in Table 3. First, the relevance of the GED is confirmed in comparison with the normal distribution. The estimated degree of parameter ν for the GED is below two, indicating that estimated normalised residuals are not normally distributed. The t-test statistics reject the null hypothesis $\nu = 2$ of normality for all sample periods. These findings confirm the earlier descriptive data analysis that departures from normality observed in the KOSPI 200 index returns. Figure 3 plots the density for the normalised residuals of all sample periods. The densities of normalised residuals for all sample periods follow the GED rather than the normal distribution. Thus, the GED seems to do a good presentation in accounting for the non-normality of normalised residuals.

Second, the volatility persistence coefficients (β) for all sample periods are highly significant at the 5% level. In particular, the estimated value of the persistence coefficient in the pre-futures period is much lower than that in the post-futures period. This implies that volatility more persistent in the post-futures period than in the pre-futures period. Due to the fact that an unusual shock might increase volatility persistence in the post-futures period, we remove the effect of this unusual volatile period and re-examine the post-futures period without the period of Korean financial crisis. Comparing the post-futures period with post-futures* period, both estimated volatility persistent coefficients are little different regardless of unusual shocks. In addition, the estimated value of the persistence coefficient in the post-futures* period is significantly higher than that in the pre-futures period. From traditional perspectives, this surprising finding may indicate that the introduction of index futures trading increases its underlying spot market volatility. However, Lamoureux and Lastrapes (1990) argued that even if volatility persistence increases, this may not be damaging to the market. It may be the result of increased information flows which enforces the market more efficient. Thus, although the introduction of index futures trading generally increases volatility persistence on the underlying market, it makes the stock market relatively more efficient because volatility shocks are more quickly assimilated in that market. A similar finding has been reported by Lee and Ohk (1992). They found an increase in volatility persistence on the behaviour of stock market returns following index futures trading.

Third, the estimated asymmetry coefficients (γ) for all sample periods are negative and significantly different from zero, which means positive return shocks usually generate less volatility than negative returns shocks. The degree of asymmetries for the post-futures period is lower than that for the pre-futures period, indicating that the introduction of index futures trading reduces the asymmetric response of volatility to news in the Korean stock market. When removing the unusual volatile period, the degree of asymmetries for the post-futures* period is lower than that for the post-futures period. The interpretation of this evidence is that financial leverage and volatility feedback effects increase asymmetries on volatility during the Korean financial crisis. Additionally, since the introduction of index futures trading, asymmetries on volatility have been significantly reduced. From this evidence, it is clear that the introduction of index futures trading has stimulated noise and feedback traders to transfer from the spot market to the futures market and then has led to an improvement in the mechanism of information transmission in the underlying spot market. For example, if noise and feedback traders overreact to news, especially bad news, then the introduction of index futures trading seems to have reduced this overreaction to news. The introduction of index futures trading also may bring more reliable information to the market, allow for quicker dissemination of information and thus stock market become more efficient. This finding is not consistent with the financial leverage and volatility feedback effects being the explanations of observed asymmetries on stock return volatility. If traditional explanations result in asymmetries on stock return volatility, the introduction of futures trading has nothing to do with the extent of any asymmetries on spot market volatility. Therefore, the introduction of index futures trading has reduced the asymmetric response of volatility to news and then stabilises the underlying spot market due to the increase in the amount of information flows. This result is consistent with that of major stock markets in which it appears that the asymmetric response of volatility to news has been reduced since the introduction of futures trading (Antoniou, Holmes and Priestley, 1998).

Fourth, the diagnostic test results of estimated models for all sample periods are presented in Table 4. The skewness and excess kurtosis are dramatically reduced in the normalised residuals for all sample periods. However, remaining skewness and excess kurtosis statistics indicate the inappropriateness of the assumption of conditional normality; the Jarque-Bera test statistics for all sample periods are statistically significant at the 5 % level, which motivates the use of generalised errors rather than conditional Gaussian errors for the estimations. Additionally, Serial correlation tests performed on the normalised residuals and squared normalised residuals present no evidence against independence. For example, the Ljung-Box $Q(12)$ and $Q_s(12)$ statistics are lower than their critical value of 21.026 at the 5% level from a chi-squared distribution with 12 degrees of freedom for all sample periods. This implies that all models can capture the time varying volatility.

However, although above diagnostic tests can capture the time varying volatility, they are not designed to test how well the model captures the asymmetry in the conditional variance, or the impact of the magnitude of positive and negative innovations on volatility. For this purpose the diagnostic tests proposed by Engle and Ng (1993) are performed in Table 4. If the volatility process is correctly specified, the squared normalised residuals should not be predictable on the basis of such observed variables as the sign, or the size of past residuals. Note that there is no significant sign bias, negative size bias in normalised residuals of all models across all sample periods. The joint test statistics for estimated models are lower than the critical value of 7.815 at the 5% level from a chi-squared distribution with 3 degrees of freedom for all models. Thus, estimated models across all sample periods are correctly specified and the estimated volatility fully incorporates asymmetries in the Korean stock market.

6. CONCLUSIONS

The issue of the impact of stock index futures trading on the underlying spot market volatility have received great attention since the stock market crash of October 1987. However, it is still unclear whether the future trading is desirable or undesirable on the underlying spot market volatility.

This study investigates the impact of stock index futures trading on the spot volatility in Korean stock market and extends the traditional analysis of examining whether index futures trading has increased stock market volatility before and after futures trading with the asymmetric response of volatility to news. There are three important conclusions in this study. First, since the GED is found to outperform the normal, it is clear that the unconditional return distribution of KOSPI 200 tend to have higher mean and fatter tails than the normal distribution. Thus, the assumption of non-normality is appropriate to modelling the conditional variance of stock returns.

Second, the estimated results suggest that the introduction of index futures trading increases the amount of information which is quickly disseminated into spot market prices. Although the increase in volatility persistence might be due to destabilising effects of futures trading associated with speculative trades in futures and options, the introduction of stock index futures provide more reliable information and improve the underlying spot market efficiency.

Third, the asymmetric response of volatility to news has been changed since the introduction of futures trading; for pre-futures period, asymmetries in stock market volatility are significantly higher than that for the post-futures period. This evidence indicates that index futures trading induce symmetry of information to traders and make the spot market more efficient. The introduction of index futures trading provides new channels of information, more information and reduction of heterogeneous traders. Thus, noise and feedback traders have been forced to be away from the spot market since the introduction of index futures trading. This phenomenon may lead to an improvement in the dynamics of the underlying market. Additionally, this finding is inconsistent with tradition explanations which the financial leverage and volatility feedback effects may be accused of the asymmetric response of volatility to news.

In summary, the introduction of index futures trading in the Korean stock market has not destabilised its spot market, has reduced observed asymmetries in stock market volatility, and thus has made the spot market more efficient. These findings may contribute implications on the appropriate regulatory regime for the Korean future markets. For example, since the introduction of index futures trading improve the spot market efficiency, the market policy or supervisory markers highlight the development and growth of futures market in terms of the introduction of new futures contracts, such as individual stock index futures and commodities futures contracts.

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Figure 1. The KOSPI 200 prices

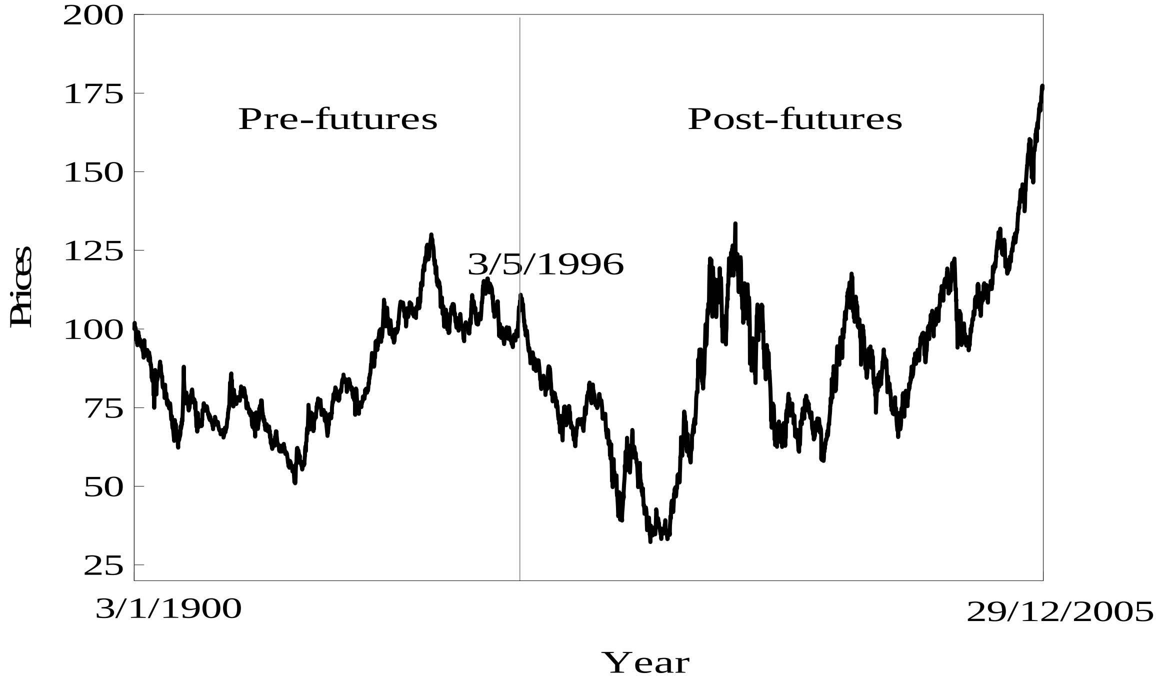


Figure 2. The KOSPI 200 returns

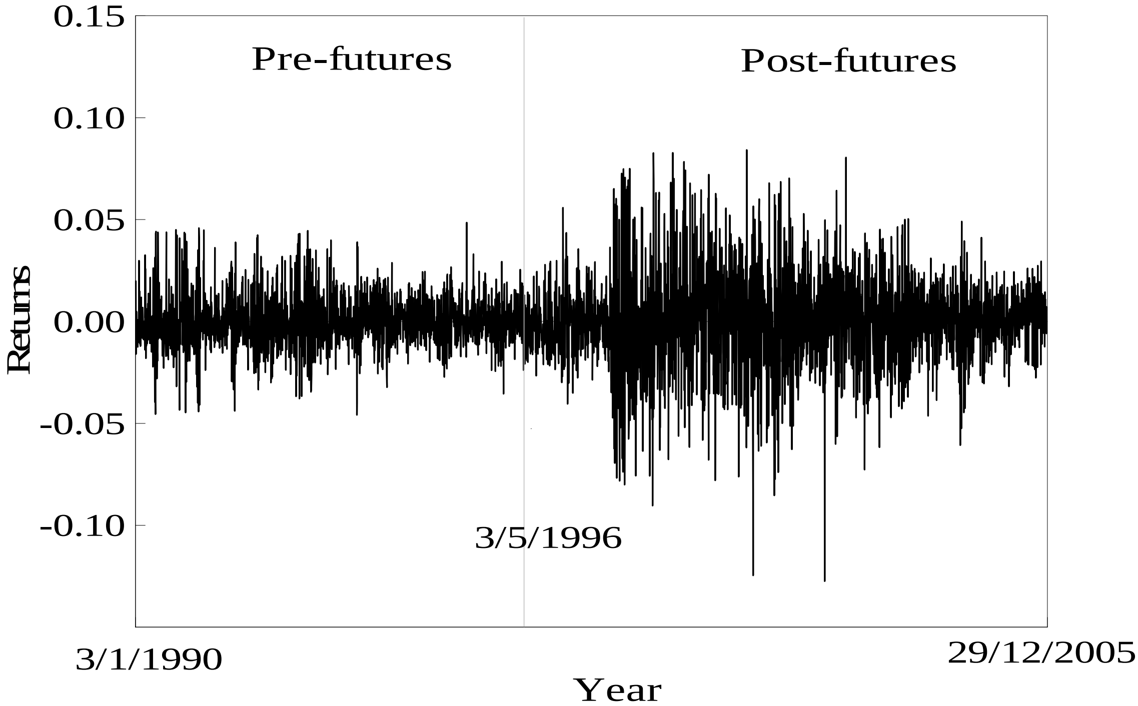
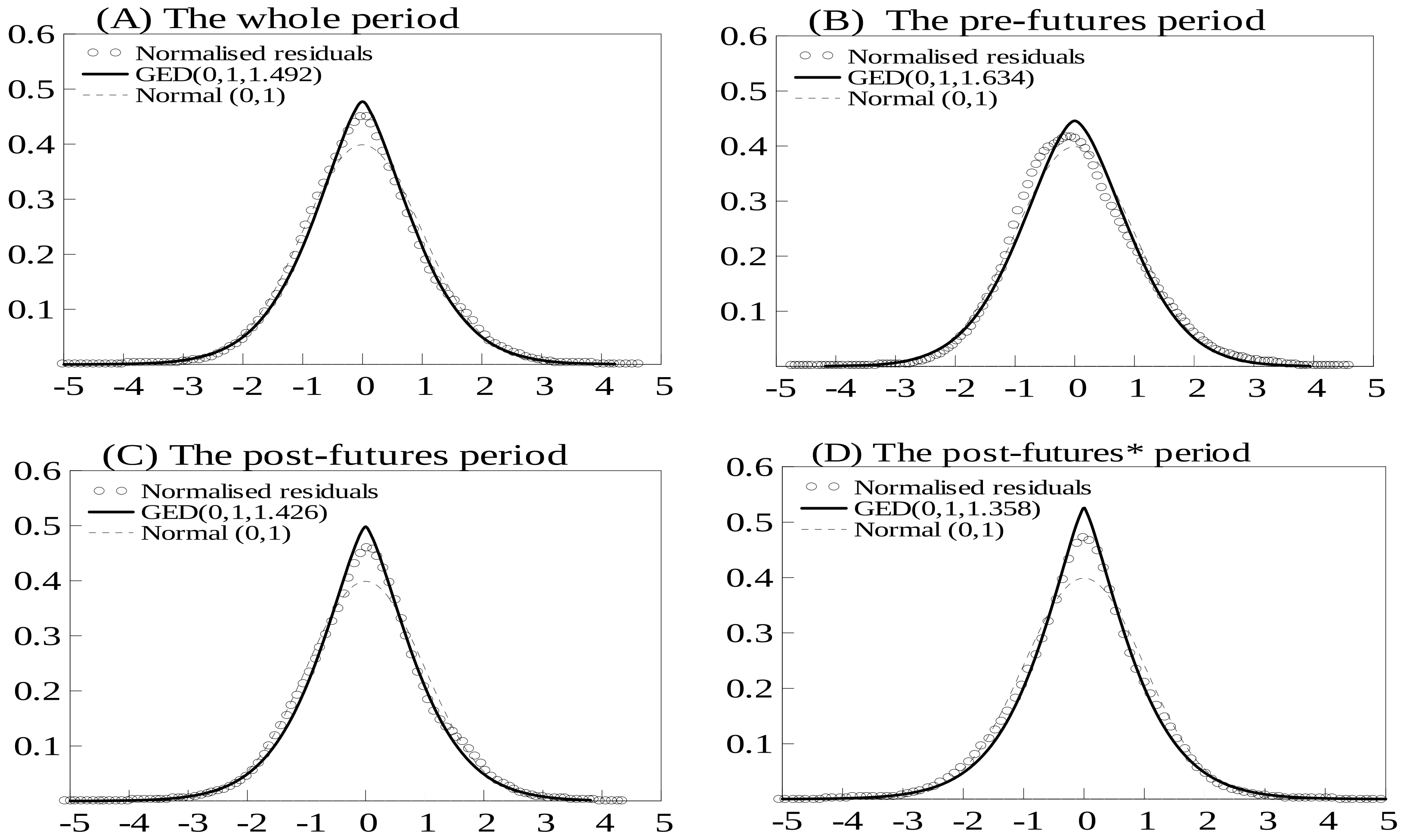


Figure 3. The density for the ARMA(n,s)-GARCH$(1,1)$ models of all sample periods



Note: the solid line of each sample period represents the density of the generalised error distribution (GED).

Table 1. Descriptive statistics for daily KOSPI 200 index returns

Statistics	**Whole period**	**Pre-futures period**	**Post-futures period**	**Post-futures* period**
Mean	0.0001	0.00004	0.0002	0.0009
Standard deviation	0.0190	0.0132	0.0223	0.0218
Skewness	-0.0437	0.3803	-0.1112	-0.2002
Kurtosis	6.2544	4.3885	5.3036	5.4084
Jarque-Bera	1928.84 (0.000)	193.95 (0.000)	558.61 (0.000)	445.32 (0.000)
$Q(12)$	59.50 (0.000)	30.67 (0.000)	41.08 (0.000)	9.58 (0.653)
$Q_s(12)$	1634.4 (0.000)	817.51 (0.000)	605.11 (0.000)	169.03 (0.000)

Notes: This table reports descriptive statistics for the sample return data. Under the null hypothesis for normality, the Jarque-Bera statistic is distributed as $\chi^2(2)$. The $Q(12)$ and $Q_s(12)$ respectively represent the Ljung-Box test statistics for return series and squared return series for up to 12th order serial correlation. P-values are presented in parentheses.

Table 2. Order selection of the ARMA(n,s)-GARCH$(1,1)$ model

ARMA (n,s)-GARCH $(1,1)$	**Whole period**	**Pre-futures period**	**Post-futures period**	**Post-futures* period**
$n=0, s=0$	-5.407204	-5.970747	-5.005235	**-4.982844**
$n=0, s=1$	-5.411413	-5.971038	**-5.010465**	-4.981102
$n=0, s=2$	-5.410889	-5.971042	-5.007894	-4.978232
$n=1, s=0$	-5.411311	-5.971418	-5.009159	-4.980575
$n=1, s=1$	**-5.412052**	**-5.974203**	-5.007040	-4.978018
$n=1, s=2$	-5.410147	-5.970950	-5.004559	-4.975595
$n=2, s=0$	-5.411598	-5.973314	-5.006485	-4.977138
$n=2, s=1$	-5.409814	-5.970568	-5.003760	-4.974479
$n=2, s=2$	-5.408227	-5.967726	-5.005121	-4.972025

Note: this table provides the values of the Schwarz Bayesian Information Criterion across the various ARMA specifications using a GARCH $(1,1)$ specification.

Table 3. ARMA(n,s)-EGARCH$(1,1)$ estimation results for the all sample periods

Mean equation: $y_t = \mu + \phi_1 y_{t-1} + \varepsilon_t + \theta_1 \varepsilon_{t-1}$

Variance equation: $\log(h_t) = \omega + \beta \log(h_{t-1}) + \alpha \left[\frac{|\varepsilon_{t-1}|}{\sqrt{h_{t-1}}} - E\left| \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} \right| \right] + \gamma \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}$

Periods	**Whole period**		**Pre-futures period**		**Post-futures period**		**Post-futures* period**	
Models	**ARMA(1.1)-EGARCH(1.1)**		**ARMA(1.1)-EGARCH(1.1)**		**MA(1)-EGARCH(1.1)**		**EGARCH(1.1)**	
Distribution	**Normal**	**GED**	**Normal**	**GED**	**Normal**	**GED**	**Normal**	**GED**
μ	0.005 [0.163]	-0.026 [-0.92]	-0.0003 [-0.77]	-0.0007 [-1.81]	0.0003 [0.70]	-0.0003 [0.88]	0.001** [3.07]	0.001** [3.63]
ϕ_1	-0.353** [-2.769]	-0.342** [-2.51]	-0.523** [-3.29]	-0.500** [-3.21]				
θ_1	-0.444** [-3.642]	-0.431** [-3.28]	-0.613** [-4.17]	-0.594** [-4.13]	-0.099** [-3.19]	-0.083** [-4.04]		
ω	0.017** [5.609]	0.012** [3.10]	-0.912** [-5.56]	-0.908** [-4.63]	-0.065** [-3.19]	-0.066** [-2.45]	-0.083** [-3.07]	-0.067** [-2.01]
α	0.194** [15.19]	0.197** [11.41]	0.380** [10.24]	0.385** [8.53]	0.152** [9.60]	0.146** [6.94]	0.149** [8.08]	0.137** [5.38]
β	0.989** [435.45]	0.988** [315.19]	0.896** [48.23]	0.897** [40.42]	0.991** [384.93]	0.992** [292.63]	0.989** [287.87]	0.991** [234.98]
γ	-0.042** [-7.37]	-0.043** [-5.18]	-0.064** [-3.33]	-0.068** [-3.00]	-0.035** [-5.51]	-0.037** [-3.86]	-0.031** [4.59]	-0.028** [-2.61]
ν		1.492** [39.82]		1.634** [21.40]		1.426** [30.88]		1.358** [26.56]
log likelihood	-8243.95	-8198.66	5564.99	5573.76	6286.81	6322.01	4481.37	4516.92

Note: The t-statistics are presented in brackets. ** indicates significant at the 5 % level.

Table 4. Diagnostic test results for ARMA(n,s)-EGARCH$(1,1)$ estimation

Periods	**Whole period**		**Pre-futures period**		**Post-futures period**		**Post-futures* period**	
Models	**ARMA(1.1)-EGARCH(1.1)**		**ARMA(1.1)-EGARCH(1.1)**		**MA(1)-EGARCH(1.1)**		**EGARCH(1.1)**	
Distribution	**Normal**	**GED**	**Normal**	**GED**	**Normal**	**GED**	**Normal**	**GED**
Skewness	0.032	0.031	0.335	0.337	-0.170	-0.172	-0.300	-0.311
Excess Kurtosis	1.277	1.281	0.615	0.624	1.548	1.562	1.957	2.020
Jarque-Bera	296.95 (0.000)	298.69 (0.000)	63.98 (0.000)	65.34 (0.000)	261.87 (0.000)	266.64 (0.000)	312.97 (0.000)	333.54 (0.000)
$Q(12)$	12.414 (0.333)	12.871 (0.302)	14.672 (0.198)	14.664 (0.198)	7.640 (0.813)	8.555 (0.740)	8.228 (0.767)	8.155 (0.773)
$Q_s(12)$	17.693 (0.089)	17.431 (0.096)	17.026 (0.107)	17.289 (0.100)	11.55 (0.482)	12.216 (0.428)	9.687 (0.643)	9.915 (0.623)
Sign bias test	-0.672 (0.502)	-0.737 (0.461)	-1.669 (0.095)	-1.259 (0.208)	0.063 (0.950)	0.182 (0.856)	1.325 (0.185)	1.174 (0.241)
Negative size bias test	0.617 (0.538)	0.576 (0.564)	0.114 (0.910)	0.391 (0.696)	0.961 (0.337)	1.032 (0.302)	0.926 (0.355)	0.665 (0.506)
Positive size bias test	-1.154 (0.249)	-1.187 (0.235)	-1.390 (0.165)	-1.267 (0.205)	-1.180 (0.238)	-1.111 (0.267)	-0.600 (0.549)	-0.613 (0.540)
Joint test	0.668 (0.571)	0.695 (0.555)	1.437 (0.230)	1.094 (0.351)	0.793 (0.500)	0.803 (0.492)	1.356 (0.255)	1.210 (0.205)

Note: $Q(12)$ and $Q_s(12)$ are the Ljung-Box test statistics for 12^{th} order serial correlation of the normalised residuals and squared normalised residuals, respectively. P-values are presented in parentheses.