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Index Futures Trading and Asymmetric Volatility: Evidence from Asian Stock Markets*

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Empirical studies have suggested that information inefficiency is one of the causes of the asymmetric response of volatility to news. This paper questions whether the introduction of index futures trading will improve information efficiency and reduce volatility asymmetry in Asian stock markets. This article re-examines the impact of index futures trading on five Asian spot markets, accounting for asymmetric volatility using the GARCH, GJR-GARCH and APGARCH models. From the analysis, the asymmetry volatility is prevalent in Asian stock markets. The impact of index futures trading increases asymmetry volatility due to some speculative activities. Consequently, the results imply that the role of index futures trading in Asian stock markets is not related to the improvement of information efficiency.

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Keywords: index futures trading, asymmetric volatility, Asian stock markets, GARCH, GJR-GARCH, APGARCH

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1. INTRODUCTION

Since the stock market crash of October 1987, the issue regarding the impact of index futures trading on the underlying spot market has received attention from academic researchers and policy makers. The most controversial issue is concentrated on the stabilization or destabilization of spot markets. From an empirical perceptive, the effects whether futures index trading is desirable or undesirable on the underlying spot market have been studied with inconclusive results.[1)]

Traditionally increased volatility following the introduction of futures index trading has been interpreted as the destabilization of spot market. Such a restricted point of view 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 new information (Lee and Ohk, 1992).

Recent studies have new hypothesis that the introduction of index futures trading can reduce the asymmetric volatility of spot markets (Antoniou, Holmes and Priestley, 1998). As the introduction of index futures trading increases the large amount of information and enhances the dissemination of new information to the spot prices, this phenomenon can improve the information efficiency of the spot market and reduce the degree of the asymmetric response of volatility to new information. Therefore, index futures trading may play an important role on stabilizing the spot market through the reduction of asymmetric volatility.

The impact of index futures trading to five Asian stock markets is examined with regard to information inefficiency, asymmetries and market dynamics. To fully understand the impact of index futures trading on the underlying spot market, it is necessary to take account of the asymmetric response of volatility to news before and after index futures trading. This

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

study focuses on the asymmetric response of volatility to news before the pre- and post-futures periods to improve the mechanism of informational transmission in the Asian stock markets.

The rest of this paper is organized as follows. Section 2 reviews a theoretical background and previous literature with regard to the asymmetric response of volatility to news. Section 3 discusses characteristics of symmetric and asymmetric volatility models. Section 4 provides descriptive statistics of the sample data and the empirical results. The final section contains concluding remarks.

2. THEORETICAL BACKGROUND

Over the last two decades, the debate on the causes of asymmetric volatility in stock returns has been studied in both the theoretical and practical literature. In general, volatility tends to respond asymmetrically to the arrival of unexpected news; negative shocks (bad news) appear to generate more volatility than positive shocks of the same magnitude (Black, 1976; Christie, 1982; Nelson, 1991).

As first noted by Black (1976), a potential explanation for this predictive asymmetry on stock volatility is offered by the role of financial and operating leverage. For example, if the value of a leveraged firm drops, the equity will become more leveraged, causing the volatility on the rate of return by the equity to rise because the risk is positively related to firm leverage (Christie, 1982; Schwert, 1989). An alternative explanation is that a volatility feedback effect brings about asymmetries on volatility (French, Schwert, and Stambaugh, 1987; Bekaert and Wu, 2000). 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).

Studies have suggested new hypothesis that the information inefficiency is the one of reasons in generating the asymmetric volatility in the stock market. The predictive asymmetry reflects the role of market information transmission. In the contrast to the assumption of the efficient market hypothesis investors are not always rational when making decisions actions are not fully justified in terms of fundamental information, and therefore the actions can lead to asymmetries.[2)] Sentana and Wadhwani (1992) investigate the asymmetric response of volatility to news with a model of positive feedback (noise) traders possessing less information than informed counterparts. The positive feedback traders tend to respond to bad news (price falls) more, which would lead to greater volatility than a response to good news (price rises).

The introduction of index futures trading intends to reduce asymmetric information in the underlying spot market in terms of low transaction costs, easily available short positions, low margins, and rapid execution. These advantages bring private information, attract additional traders, induce symmetric information, and improve the mechanism of information transmission. The introduction of index futures trading has stimulated noise traders or feedback traders to be attracted away from the spot market to the futures market, and then observed asymmetric volatility in the spot market will be reduced following the introduction of index futures trading.

Some empirical studies are in agreement with the new hypothesis that the introduction of index futures trading may reduce the asymmetric volatility of the underlying spot markets (Subrahmanyam, 1991; Gorton and Pennacchi, 1993; Antoniou, Holmes, and Priestley, 1998). For example, Antoniou, Koutmos, and Pericli (2005) find that the introduction of index futures trading reduces the impact of positive feedback trading due to the migration

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[2)] These traders are regarded as ‘noise traders’ or ‘uninformed investors’ since the trading strategies are based on noise and not on market information (Black, 1986). Such 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 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).

of feedback traders from the spot to futures markets and attracts rational investors who make the market more efficient.

As the introduction of index futures trading is new phenomenon in the Asian stock markets, only small proportion of the literature has studied the role of index futures trading in the Asian stock markets with inconclusive results. Gulen and Mayhew (2000) compare the impact of index futures trading in some Asian stock markets (Japan, Korea, Hong Kong, and Malaysia). The evidence suggests that the volatility of Hong Kong and Malaysian markets is reduced while the volatility of Japanese market is increased after the introduction of index futures trading. There is no significant effect in the Korean market. Chiang and Wang (2002) also indicate that the introduction of index futures trading increases volatility asymmetry in the Taiwan stock market. They suggest that the increased volatility asymmetry can be caused by speculative trading from the majority of non-institutional investors.

On the other hand, Byun and Jo (2003) and Byun, Jo and Cheong (2003) examine empirically asymmetries on volatility before and after the introduction of KOSPI 200 Index futures trading using threshold GARCH (TGARCH) and GJR-GARCH models, respectively. The evidence indicates that the introduction of index futures trading leads to the easing of asymmetries on volatility, implying that information inefficiency is appropriate as one of the causes of the asymmetric volatility of the Korean stock market. Park (2006) also examines asymmetries on volatility before and after the introduction of KOSPI 200 Index futures trading using the GJR-GARCH model. The results of this paper show that leverage effect can be a good candidate for explaining the volatility asymmetry of Korean stock market.

Empirical studies on the impact of index futures trading show no agreement in explaining asymmetric volatility in the Asian stock markets. This paper re-examines the impact of index futures trading on stock market volatility considering the asymmetric volatility. Examining the asymmetric response of volatility to news can provide an insight into the role of market dynamics in Asian stock markets. Therefore, the analysis will provide important guidance on the appropriate regulatory regime for the Asian futures markets.

3. METHODOLOGY

To analyze the impact of futures index trading on the underlying market volatility, we employ GARCH, GJR-GARCH and asymmetric power GARCH (APGARCH) models. In particular, the simple GARCH model of Bollerslev (1986) only forecasts a symmetric feature of volatility, while the GJR-GARCH and APGARCH models are to measure the asymmetric response of volatility to news (Engle and Ng, 1993). A simple GARCH(1,1) model can be expressed as follows

$$\varepsilon_t = \sqrt{h_t}\upsilon_t, \tag{1}$$

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

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

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 h_t depends not only upon information about volatility during the previous period ($\alpha_1 \varepsilon_{t-1}^2$) but also on the fitted variance from the model during the previous period ($\beta_1 h_{t-1}$). For example, investors estimate the forecast variance from the last period (the GARCH term β_1), and information about volatility observed in the previous period (the ARCH term α_1). If the return series is unexpectedly large in either the upward or the downward direction, then investors will increase the estimate of the variance of the next period. 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 (ε_{t-1}^2) in equation (4) has a symmetric impact on volatility irrespective of good news or bad news. Engel and Ng (1993) argue 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 account for this problem, Glosten, Jagannathan and Runkle (1993) propose an asymmetric GARCH model, the GJR-GARCH model. From equation (3), the conditional variance function of a GJR-GARCH(1, 1) model is specified as

$$h_t = \omega + \alpha_1 \varepsilon_{t-1}^2 + \gamma_1 \varepsilon_{t-1}^2 D_{t-1} + \beta_1 h_{t-1}, \tag{4}$$

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 $\gamma_1 D_{t-1}$ dummy variable 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 impact on volatility, while bad news has an $\alpha_1 + \gamma_1$ impact on volatility. So if $\gamma_1 > 0$, the GJR-GARCH model can capture an asymmetric effect. If $\gamma_1 = 0$, the GJR-GARCH model becomes the simple GARCH model.

In addition, the APGARCH model of Ding, Ganger, and Engle (1993) extends the GARCH model of Bollerslev (1986) with an optimal power transformation term in the lagged errors (ε_{t-i}). The GARCH model commonly imposes a squared power term in the lagged errors. The squared power term may not be optimal to capture volatility clustering (Ding, Granger, and Engle, 1993). The general APARCH(1, 1) model is given as

$$\sigma_t^\delta = \omega + \alpha_1 \left(\left| \varepsilon_{t-1} \right| - \gamma_1 \varepsilon_{t-1} \right)^\sigma + \beta_1 \sigma_{t-1}^\delta, \tag{5}$$

where ω, α_1, γ_1, β_1, and δ are parameters. The coefficient $\delta(\delta > 0)$ is a coefficient for the power term, whereas $\gamma_1(-1 < \gamma_1 < 1)$ accounts for asymmetric volatility in which positive and negative returns of the same magnitude do not generate an equal response in volatility.

4. EMPIRICAL RESULTS

4.1. Data and the Descriptive Statistics

The data sets consist of daily closing prices for the five Asian stock market indices: TOPIX (Japan), KOSPI 200 (Korea), KLCI (Malaysia), Straits Times (Singapore) and TAIEX (Taiwan).[3] Table 1 reports the commence date of index futures and the data period for each country over 10 years along with the number of observations in the whole period.

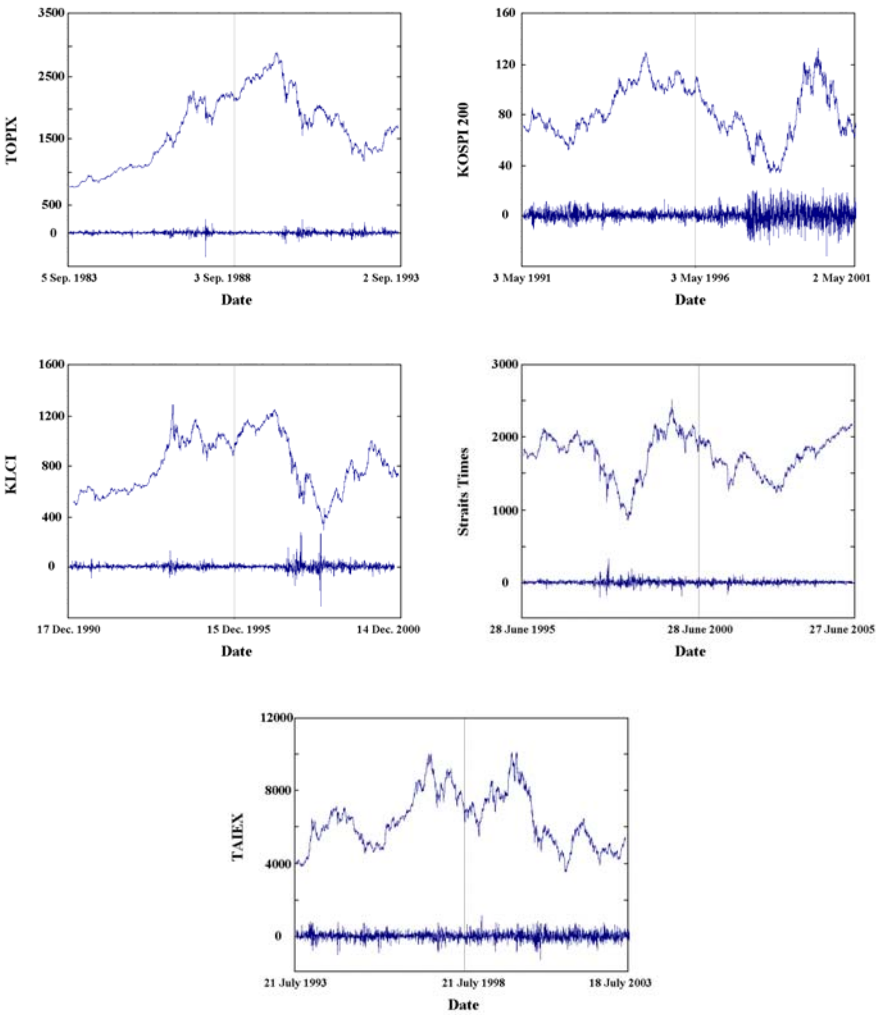
Daily price series are converted into the nominal percentage return series for all sample indices, i.e. $y_t = 100\ln(P_t / P_{t-1})$ for $t = 1, 2, \ldots, T$, where y_t is the returns for each index at time t, and P_t is the current price and P_{t-1} is the price from the previous day. Figure 1 displays the dynamics of all sample

Table 1 Data Description and Data Periods

Data	Launch Date	Data Period	Observations
TOPIX	3 Sep. 1988	5 Sep. 1983 - 2 Sep. 1993	2,466
KOSPI 200	3 May 1996	3 May 1991 - 2 May 2001	2,820
KLCI	15 Dec. 1995	17 Dec. 1990 - 14 Dec. 2000	2,478
Straits Times	28 June 2000	28 June 1995 - 27 June 2005	2,511
Taiwan	21 July 1988	21 July 1993 - 18 July 2003	2,447

[3] All sample index data are obtained from the database of DataStream.

Figure 1 Graphs of Sample Indices for Prices and Returns



indices and returns. A vertical line represents the introduction date of futures market and divides an entire period into two periods such as pre-future and post-future periods. [4)]

[4)] To avoid the data confusing effect, each sub-period contains the five-year daily observations before and after index futures trading.

Descriptive statistics for all sample returns are summarized in table 2. All sample returns show a similar pattern of results in the pre-future and post-futures periods. The sample mean of returns is very small and the corresponding standard deviation of returns is higher. All sample returns display high measures of skewness and excess kurtosis, indicating that they do not correspond with the assumption of normal distribution.[5] Such excess kurtosis and skewness are common characteristics of return distributional properties, which appear to be leptokurtosis. Likewise, the Jarque-Bera (J-B) statistics also confirm that the null hypothesis of normality should be rejected at the 1% significant level.

According to the Ljung-Box test statistics $Q(12)$, the null hypothesis of serial independence for all sample returns is rejected at the 1% significance level, expect for the Straits Times and TAIEX returns. This evidence implies that the impact of non-synchronous trading on returns results in serial correlation in return series and it is possible for predicting future returns from past returns. Additionally, the $Q_s(12)$ statistics to check the correlation of squared returns suggest significant evidence of serial correlation in the variance for all sample returns. The distribution of the next squared return depends on not only the current squared return but also several previous squared returns which results in volatility clustering. These findings imply that there are non-normality, serial correlation, and volatility clustering in stock returns.

All sample return series display significant serial dependence due to non-synchronous phenomena in the markets expect for the Straits Times and TAIEX returns. To overcome this drawback, a standard autoregressive moving average (ARMA) model is considered for the conditional mean equation, assuming the standard GARCH(1, 1) model. Note that lag order selection issues are important when building parsimonious models for all period return series.

[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.

Table 2 Descriptive Statistics of Return Series

Pre-futures Period					
	TOPIX	KOSPI 200	KLCI	Straits Times	TAIEX
Obs.	1,235	1,470	1,238	1,256	1221
Mean	0.092	0.027	0.056	0.011	0.059
Standard Deviation	1.061	1.247	1.214	1.644	1.539
Skewness	–2.291	0.278	0.150	0.540	–0.222
Excess Kurtosis	46.64	0.943	7.118	10.32	2.720
J-B	113034**	73.37**	2618.0**	5639.6**	386.36**
$Q(12)$	46.63**	29.10**	41.95**	57.60**	15.35
$Q_s(12)$	136.37**	506.06**	492.85**	277.62**	156.07**

Post-futures Period					
	TOPIX	KOSPI 200	KLCI	Straits Times	TAIEX
Obs.	1,231	1,350	1,240	1,255	1226
Mean	–0.017	–0.029	–0.027	0.005	–0.033
Standard Deviation	1.260	2.584	2.269	1.122	1.899
Skewness	0.366	0.022	0.556	–0.292	0.086
Excess Kurtosis	6.373	1.352	25.82	3.501	1.404
J-B	2110.8**	103.00**	34516**	658.92**	102.19**
$Q(12)$	63.21**	38.21**	36.82***	24.96	20.91
$Q_s(12)$	135.*	274.80**	582.56***	191.03**	116.38**

Notes: This table reports following descriptive statistics: mean, standard deviation, skewness, excess kurtosis and Jarque-Bera (J-B) test and Ljung-Box test for all sample return series. Under the null hypothesis for normality, the Jarque-Bera statistic is distributed as $\chi^2(2)$. In the columns for $Q(12)$ and $Q_s(12)$, the Ljung-Box test statistics for returns and squared returns are reported up to 12^{th} order of serial independence. ** indicates the rejection of *t*-statistics at the 5% significance level.

To determine the orders n and s of the ARMA(n, s) model the paper 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 Criterion (SBIC).[6] Table 3 reports the order selection of ARMA(n, s)-GARCH(1, 1) models based on the values of the SBIC.[7] If a particular specification has a minimum SBIC value it is possible to conclude that the specification is the best one. In the case of pre-futures period, an MA (1) specification has been retained for all sample returns expect for the TAIEX returns. In the case of post-futures period, an MA (1) specification has been chosen for the TOPIX and KOSPI returns, and an AR (1) specification has been selected for the KLCI returns, while the Straits Times and TAIEX do not require the inclusion of ARMA components in the conditional mean equation.

4.2. The Impact of Index Futures Trading in the Asian Stock Markets

To assess the impact of index futures trading in the Asian stock markets three models are used to investigate predictable volatility: the GARCH model, the GJR-GARCH model and the APGARCH model. Tables 4, 5 and 6 report the estimation results of above models in the pre-futures and post-futures periods.

The Ljung-Box $Q(12)$ and $Q_s(12)$ statistics tests performed on the standardized residuals and squared standardized residuals report no evidence against independence at the 5% significance level except for the pre-futures period of KOSPI 200. The Engle LM ARCH test statistics are insignificant, indicating that there is no remaining ARCH effect in the all standardized residuals. This implies that both estimated models are correctly specified to capture the time varying volatility.

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

[7] Estimation of ARMA(n, s)-GARCH(1, 1) models are based on the Brendt, Hall, Hall, and Hausman (BHHH) algorithm for obtaining maximum likelihood estimates.

Table 3 Order Selection of the ARMA(*n*, *s*)-GARCH(1, 1) Model

Pre-futures Period

ARMA(*n*, *s*)-GARCH(1, 1)	TOPIX	KOSPI 200	KLCI	Straits Times	TAIEX
$n=0,\ s=0$	2.543707	3.164132	2.975612	3.421647	**3.628690**
$n=0,\ s=1$	**2.487657**	**3.162659**	**2.938073**	**3.395960**	3.634458
$n=0,\ s=2$	2.492783	3.166248	2.941876	3.400856	3.637442
$n=1,\ s=0$	2.497346	3.166042	2.938482	3.397359	3.635847
$n=1,\ s=1$	2.492846	3.164617	2.944065	3.402821	3.639694
$n=1,\ s=2$	2.500670	3.169303	2.948901	3.408098	3.644523
$n=2,\ s=0$	2.495835	3.169863	2.945150	3.404199	3.640358
$n=2,\ s=1$	2.493578	3.174296	2.950778	3.408260	3.645196
$n=2,\ s=2$	2.498687	3.173156	2.955984	3.413721	3.642719

Post-futures Period

ARMA(*n*, *s*)-GARCH(1, 1)	TOPIX	KOSPI 200	KLCI	Straits Times	TAIEX
$n=0,\ s=0$	2.943906	4.526721	3.778628	**2.942451**	**4.069451**
$n=0,\ s=1$	**2.924734**	**4.514810**	3.769035	2.948036	4.072411
$n=0,\ s=2$	2.930512	4.519455	3.772148	2.952904	4.076023
$n=1,\ s=0$	2.927806	4.518027	**3.768660**	2.948920	4.074504
$n=1,\ s=1$	2.932549	4.521434	3.774046	2.953331	4.077559
$n=1,\ s=2$	2.938008	4.524880	3.778675	2.957579	4.083117
$n=2,\ s=0$	2.932979	4.522680	3.774589	2.954350	4.077979
$n=2,\ s=1$	2.936543	4.526860	3.779995	2.958657	4.083609
$n=2,\ s=2$	2.942373	4.531648	3.782609	2.960468	4.089396

Notes: This table provides the values of the Schwarz Bayesian Information Criterion across the various ARMA specifications using a GARCH(1, 1) specification. The bold types mean the minimum SBIC and the specification is the best for each index return series.

Table 4 Estimation Results for the GARCH Model

	TOPIX		KOSPI 200		KLCI		Times Straits		TAIEX	
	Pre	Post	Pre	Post	Pre	Post	Pre	Post	Pre	Post
μ	0.122	0.070	0.030	–0.074	0.074	0.033	0.009	0.045	0.074	–0.004
	(0.028)**	(0.028)**	(0.029)	(0.056)	(0.033)**	(0.042)	(0.039)	(0.027)	(0.040)	(0.051)
θ_1	0.304	0.174	0.067	0.140	0.223					
	(0.029)**	(0.031)**	(0.028)**	(0.029)**	(0.030)**					
ϕ_1						0.145	0.191			
						(0.031)**	(0.030)**			
ω	0.039	0.034	0.100	0.019	0.057	0.043	0.031	0.019	0.108	0.197
	(0.007)**	(0.007)**	(0.025)**	(0.009)**	(0.012)**	(0.008)**	(0.006)**	(0.006)**	(0.021)**	(0.061)**
α_1	0.302	0.168	0.142	0.059	0.136	0.150	0.150	0.094	0.070	0.091
	(0.012)**	(0.018)**	(0.024)**	(0.009)**	(0.016)**	(0.016)**	(0.015)**	(0.010)**	(0.009)**	(0.019)**
β_1	0.715	0.821	0.794	0.941	0.824	0.849	0.850	0.897	0.884	0.856
	(0.012)**	(0.018)**	(0.032)**	(0.009)**	(0.019)**	(0.013)**	(0.012)**	(0.009)**	(0.014)**	(0.031)**
$\log(L)$	–1518.33	–1782.39	–2307.41	–3029.48	–1800.86	–2316.88	–2114.82	–1832.12	–2201.10	–2480.35
$Q(12)$	6.98	6.67	20.85**	8.92	8.46	4.93	12.36	18.56	14.64	15.36
$Q_s(12)$	7.28	8.71	12.08	10.16	7.94	4.20	14.79	9.28	13.62	16.73
ARCH(5)	1.033	0.175	0.875	1.486	0.576	0.325	1.306	1.592	1.109	1.645
$\alpha_1+\beta_1$	1.017	0.989	0.916	1.000	0.960	0.999	1.000	0.991	0.954	0.947

Notes: Standard errors are indicated in parentheses below the corresponding parameter estimates. The $\ln(L)$ is the maximized Gaussian log likelihood. ARCH (5) represents the F-statistic of the ARCH test with lag 5, based on the standardized residuals. **indicates rejection of the null hypothesis at the 5% significance level. See table 2.

Table 5 Estimation Results for the GJR-GARCH Model

	TOPIX		KOSPI 200		KLCI		Times Straits		TAIEX	
	Pre	Post	Pre	Post	Pre	Post	Pre	Post	Pre	Post
μ	0.083 (0.028)**	0.017 (0.027)	0.011 (0.031)	–0.104 (0.058)	0.050 (0.035)	–0.015 (0.043)	–0.018 (0.039)	0.016 (0.027)	0.056 (0.041)	–0.041 (0.051)
θ_1	0.285 (0.029)**	0.188 (0.031)**	0.065 (0.028)**	0.136 (0.135)**	0.226 (0.030)**		0.200 (0.031)**			
ϕ_1						0.149 (0.043)**				
ω	0.037 (0.006)**	0.026 (0.005)**	0.091 (0.024)**	0.014 (0.009)	0.057 (0.012)**	0.040 (0.007)**	0.033 (0.006)**	0.015 (0.005)**	0.146 (0.026)**	0.184 (0.052)**
α_1	0.118 (0.022)**	0.041 (0.010)**	0.099 (0.023)**	0.033 (0.010)**	0.081 (0.015)**	0.077 (0.013)**	0.095 (0.095)**	0.032 (0.012)**	0.052 (0.012)**	0.016 (0.012)
β_1	0.749 (0.012)**	0.848 (0.013)**	0.805 (0.031)**	0.948 (0.008)**	0.833 (0.022)**	0.858 (0.012)**	0.857 (0.012)**	0.912 (0.010)**	0.855 (0.016)**	0.869 (0.028)**
γ_1	0.281 (0.028)**	0.210 (0.013)**	0.082 (0.033)**	0.042 (0.013)**	0.093 (0.022)**	0.136 (0.025)**	0.094 (0.020)**	0.097 (0.012)**	0.061 (0.017)**	0.138 (0.028)**
$\log(L)$	–1502.01	–1750.54	–2304.02	–3025.21	–1795.36	–2304.67	–2108.64	–1818.89	–2197.27	–2461.93
$Q(12)$	9.03	9.17	20.05**	8.41	9.25	6.71	11.61	16.49	16.67	18.18
$Q_s(12)$	8.03	17.30	12.03	9.67	6.85	4.17	16.14	6.913	15.07	14.96
ARCH (5)	1.191	0.684	0.975	1.487	0.294	0.340	1.341	1.146	0.611	1.740
Asymmetry Ratio	0.295	0.163	0.547	0.440	0.466	0.362	0.503	0.248	0.460	0.104

Notes: The asymmetry ratio $(\alpha_1/(\alpha_1+\gamma_1))$ measures the ratio of good news impact on volatility and the bad news impact volatility. See table 4.

Table 6 Estimation Results for the APGARCH Model

	TOPIX		KOSPI 200		KLCI		Times Straits		TAIEX	
	Pre	Post	Pre	Post	Pre	Post	Pre	Post	Pre	Post
μ	0.084 (0.028)**	–0.018 (0.027)	0.011 (0.031)	–0.108 (0.059)	0.054 (0.035)	–0.008 (0.039)	–0.026 (0.038)	0.008 (0.027)	0.056 (0.041)	–0.050 (0.049)
θ_1	0.288 (0.029)**	0.188 (0.028)**	0.065 (0.029)**	0.156 (0.028)v	0.225 (0.030)**		0.192 (0.030)**			
ϕ_1						0.117 (0.027)**				
ω	0.032 (0.006)**	0.032 (0.123)**	0.087 (0.024)**	0.007 (0.007)	0.055 (0.011)**	0.028 (0.005)**	0.028 (0.005)**	0.014 (0.004)**	0.180 (0.054)**	0.106 (0.031)**
α_1	0.225 (0.022)**	0.123 (0.012)**	0.140 (0.024)**	0.067 (0.010)**	0.132 (0.020)v	0.143 (0.012)**	0.143 (0.015)**	0.070 (0.012)**	0.067 (0.016)**	0.086 (0.018)**
β_1	0.742 (0.015)**	0.878 (0.012)**	0.810 (0.032)**	0.947 (0.008)**	0.840 (0.019)**	0.876 (0.011)**	0.872 (0.012)**	0.932 (0.010)**	0.848 (0.020)**	0.874 (0.025)**
γ_1	0.271 (0.042)**	0.639 (0.058)**	0.148 (0.062)**	0.243 (0.080)**	0.187 (0.045)**	0.333 (0.049)**	0.208 (0.050)**	0.541 (0.102)**	0.163 (0.053)**	0.638 (0.025)**
δ	2.331 (0.261)**	0.867 (0.160)**	1.814 (0.472)**	1.098 (0.256)v	1.664 (0.323)**	0.896 (0.137)**	1.355 (0.192)**	1.089 (0.242)**	2.445 (0.439)**	0.927 (0.303)**
$\log(L)$	–1501.63	–1740.22	–2303.94	–3025.10	–1794.97	–2291.77	–2105.97	–1815.62	–2197.03	–2457.39
$Q(12)$	8.912	11.92	20.20**	7.24	9.213	6.71	11.20	17.14	16.80	19.62
$Q_s(12)$	8.287	27.76**	12.16	10.41	6.818	4.17	16.53	11.27	15.19	17.49
ARCH (5)	1.161	1.231	1.018	1.659	0.306	0.475	1.539	1.570	0.647	2.159

Note: See table 4.

Beginning with the GARCH model in the pre-futures and post-futures periods, the estimates of α_1 and β_1 are statistically positive, indicating that the unexpected positive and negative returns result in the same size impact on volatility. This implies that the GARCH model can not capture volatility asymmetry in the Asian stock returns. In addition, the sum of α_1 and β_1 is close to unity in both periods, corresponding to persistence in the conditional variance. For example, the sum of α and β of the pre-futures period for TOPIX is over 1, indicating infinite persistence and violating the condition of the GARCH model in the conditional variance.

In the all stock returns the asymmetric coefficients (γ_1) of GJR-GARCH model are positive and significant at the 5% level, implying that an unexpected negative returns increase volatility more than unexpected positive returns of the same magnitude. This finding shows that the GJR-GARCH model outperforms the GARCH model in capturing the volatility asymmetry of Asian stock returns. To address the issue of impact of futures trading on stock market volatility, the asymmetry ratio $(\alpha_1/(\alpha_1+\gamma_1))$ of the pre-futures period is stronger than that of the post-futures period, implying that the introduction of index futures trading induces more volatility asymmetry in the post-futures period for all stock returns. This finding is inconsistent with that of major stock markets including the Japanese case in which it appears that volatility asymmetry has been reduced following index futures trading (Antoniou, Holmes and Priestley, 1998).

The APGARCH model provides more flexibility of analyzing the asymmetry volatility. For example, the power coefficients (δ) range between 2.445 and 9.867, implying that squared error term does not fit in the conditional variance specification for all the cases. Furthermore, the asymmetry coefficient (γ_1) of all stock indices is positive and significant, but the post-futures period for all stock returns show increased volatility asymmetry because of the higher degree of the coefficient in the post-futures period. This evidence confirms that the introduction of futures index trading increase asymmetry volatility in Asian stock markets.

5. CONCLUSIONS

Over the past two decades, the advent of index futures instruments has been widely spread around the Asian stock market. Although the growing body of empirical studies shows the empirical results on the impact of index futures trading, there is no agreement on the issue of the stabilizing or destabilizing role of futures market. This article has re-examined the impact of index futures trading in the five Asian stock markets accounting for asymmetric volatility.

Empirical analysis provides two main conclusions. First, the paper examined the asymmetric volatility of the spot markets before and after the introduction of index futures trading. The results indicated that all Asian stock markets show the asymmetric response of volatility to positive and negative news in the pre-futures and post-futures periods. Second, asymmetric volatility has increased in the post-futures period, indicating that the introduction of index futures trading does not contribute to the improvement of information transmission in the spot markets.

The introduction of index futures trading is not a sole vehicle to improve the mechanism of information transmission in Asian stock markets. In addition, earlier studies regarding the impact of index futures trading must be re-examined using more powerful methods in explaining the cause of asymmetry volatility in Asian stock markets.

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