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AUTHORS

Yung-Shi Liao
Chun-Fan You

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Yung-Shi Liao (Taiwan), Chun-Fan You (Taiwan)

The transitory and permanent components of return volatility in Asian stock markets

Abstract

Motivated by the asymmetric volatility phenomenon that investors respond more strongly to bad news than to good news, this study utilizes stock index returns from seven Asian markets to test whether there is any change in asymmetric volatility during Asian financial crisis. Specifically, the authors examine the transitory and permanent components of return volatility through the asymmetric component generalized autoregressive conditional heteroskedasticity (AC-GARCH) model and empirical results show that both volatility components have displayed an increasing sensitivity to bad news after the crisis, especially the transitory part. In essence, it is consistent with Schwert's (1990) market crash study and has special implications for both regulatory and practical purposes, i.e., the government should not overly intervene market turbulence because the volatility reverts to its normal level quickly after the crash.

Keywords: volatility, financial crisis, AC-GARCH model.

JEL Classification: G01, G10.

Introduction

The asymmetric responses of volatility to return shocks and the volatility components have been continuously documented in the literature for various financial assets (Speight and McMillan, 2000; Balaban and Bayar, 2005; Byrne and Davis, 2005; Kian and Kuan, 2006). The asymmetric volatility demonstrates that negative return shocks resulting from bad news appear to cause more volatility than positive return shocks resulting from good news (see Christie, 1982; Koutmos, 1999; Blasco et al., 2002; Leevess, 2007). At first, academics attribute this phenomenon to firms' financial leverage, i.e., the declining security prices would produce a higher debt to equity, resulting in an increase in the volatility of equity. Black (1976) pioneered the asymmetric volatility study and attributed it to firms' leverage effect. Lately, some scholars propose volatility feedback being the reason for asymmetric volatility. For instance, Bekaert and Wu (2000) and Wu (2001) argue that if market risk premium is an increasing function of expected volatility, an expected increase in volatility raises the required return on equity, leading to an instant stock price decline. Meantime, both studies provide evidence that volatility feedback dominates the leverage effect.

The component volatility demonstrates that the volatility could be decomposed into a transitory or short-run and a permanent or long-run component¹. Engle and Lee (1993) applied the component generalized autoregressive conditional heteroskedasticity (C-GARCH) model to assess the mean reversion of volatility in US and Japanese stock markets and found the transitory component had a strong force pulling the volatility back to its permanent component.

Moreover, Summers (1986) demonstrated that a slow mean-reverting component with transitory volatility might be the cause of excess volatility². Recently, Shively (2007) finds that transitory shocks account for as much as 68% of the shocks in the negative-return high-volatility regime and less than 4% of the shocks in the positive-return regime. When the two regimes are examined based upon volatility, the standard deviation of stock returns is around 43% higher in the negative-return regime than in the positive-return regime.

Given the market turbulence will change investors' risk attitude toward financial assets, Yang and You (2003) have examined the Asian stock return volatility during Asian financial crisis period. This paper extends their study about the characteristics of decreasing absolute risk aversion to decompose the volatility increases in the post-crisis period³. The decreasing absolute risk aversion indicates that investors have become more risk averse after the Asian financial crisis due to the great wealth shrink, thus they overweigh more severely the potentials of negative shocks. In addition, Schwert (1990) and Engle and Mustafa (1992) detect that while stock return volatility is high right after the October 1987 crash, it reverts to normal levels swiftly at the end of 1987. Kim and Kim (1996) further provide evidence that the speculative bubbles of 1987 is an example of unusually large transitory shocks that are short-lived.

This paper differs from earlier studies in the following ways. While many studies examine the effects of financial turmoil on total volatility (see for example,

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¹ Chou (1988) and Pagan and Schwert (1990) point that stock return volatility is a non-stationary process. Therefore, the finding of a unit-root in the volatility process shows that there is a transitory and a stochastic trend component in stock return volatility.

² Using a standard dividend-discount model to decide fundamental value, LeRoy and Porter (1981) and Shiller (1981) demonstrate that the stock prices are much more volatile than the underlying stream of dividend cash flows. This phenomenon is called excess volatility.

³ Pratt (1964) indicates the absolute risk aversion is decreasing in wealth and the risk premium and investors' wealth are in the opposite direction. Both Campbell and Cochrane (1999) and Fang (2001) support this decreasing absolute risk aversion.

Schwert, 1990; Engle and Mustafa, 1992), this paper emphasizes both the asymmetric volatility and volatility components of stock returns during the Asian financial crisis. In essence, the asymmetric component generalized autoregressive conditional heteroskedasticity (AC-GARCH) model makes it possible to detect whether there is any change in both permanent and transitory volatility during this particular window. The empirical results show that a rising degree of transitory and permanent asymmetric volatility has been exhibited right after the Asian financial crisis, especially the short-run part. The transitory volatility, however, dropped slowly afterwards, which means that the regulatory authority should not overly intervene during market turbulence because volatility reverts back to its normal level after a crash.

The remainder of this paper is organized as follows. Section 1 describes the data and methodology. Section 2 then reports and compares the empirical results for the pre- and post-crisis period as well as for the reversion period. Finally, concluding remarks and suggestions for future research are presented in the last section.

1. Data and research design

This study uses closing prices for the stock indexes of Hong Kong (HK), Japan (JPN), South Korea (KOA), Malaysia (MAL), Singapore (SIG), Taiwan (TWN) and Thailand (THA). The data has been retrieved from Datastream and study period extends from January 3,

1994 to June 30, 2004. Since Thai Baht's one-day devaluation of 17% on July 2, 1997 ignited the Asian financial crisis, the whole period is accordingly partitioned into three nearly equal sub-periods: the pre-, post-crisis and reversion period to alleviate the structural break problem. It is worth mentioning that, in order to observe whether the change of volatility is a transitory phenomenon, this study defines the third sub-period, call reversion period. The pre-crisis period covers from January 3, 1994 to July 1, 1997 and the post-crisis period starts from July 2, 1997 to December 31, 2000, with the reversion period begins from January 2, 2001 and ends on June 30, 2004.

Daily index returns' descriptive statistics of the three sub-periods are listed on Table 1. The mean return ranges from -0.1272 in Thailand to 0.0435 in Taiwan for the pre-crisis sub-period. The mean returns for each market are negative after the crisis period except for Singapore. In reversion sub-period, Thailand exists the maximum mean return. Meanwhile, the volatility is higher in the post-crisis sub-period than pre-crisis and reversion sub-periods. The skewness statistics indicate that all return series are either positively or negatively skewed. The kurtosis statistics suggest departure from normality, that is, all series are highly leptokurtic. Thus, the Jarque-Bera statistics reject the normality for each return series. The unit root test result of the Augmented Dickey-Fuller (ADF) shows that all series are stationary.

Table 1. The descriptive statistics of seven daily stock return series

Market	Period	Mean	Standard deviation	Skewness	Kurtosis	JB	ADF
HK	Pre-crisis	0.0269	1.3848	-0.4101	6.3807	460***	-29.07***
	Post-crisis	-0.0007	2.3330	0.2413	10.1634	1961***	-15.92***
	Reversion	-0.0226	1.3180	-0.2475	6.2599	414***	-29.46***
JPN	Pre-crisis	-0.0126	1.0639	0.2704	8.3562	1337***	-29.00***
	Post-crisis	-0.0192	1.3363	-0.0114	5.1198	171***	-28.66***
	Reversion	-0.0083	1.3283	-0.1999	4.5604	99***	-28.99***
KOA	Pre-crisis	-0.0565	1.3323	-0.1825	7.8568	1002***	-26.87***
	Post-crisis	-0.0446	2.8644	0.0487	4.2675	61***	-27.68***
	Reversion	0.0485	1.8616	-0.4429	6.2828	440***	-29.88***
MAL	Pre-crisis	-0.0183	1.2272	0.2134	10.778	2306***	-26.52***
	Post-crisis	-0.0506	2.5856	0.5398	23.2147	15590***	-29.91***
	Reversion	0.0205	0.9260	-0.6384	9.6875	1763***	-24.84***
SIG	Pre-crisis	-0.0089	0.9527	-0.223	6.6916	525***	-25.46***
	Post-crisis	0.0002	1.8949	0.4953	10.4137	2128***	-25.84***
	Reversion	-0.0052	1.1880	-0.2598	6.3994	450***	-28.87***
TWN	Pre-crisis	0.0435	1.4286	-0.4214	6.5462	505***	-31.77***
	Post-crisis	-0.0705	1.8399	-0.0562	5.4964	238***	-29.42***
	Reversion	0.0228	1.6870	0.0506	4.0721	44***	-28.79***
THA	Pre-crisis	-0.1272	1.4556	-0.255	5.7783	303***	-26.94***
	Post-crisis	-0.0736	2.3506	0.7417	5.8058	383***	-26.55***
	Reversion	0.0960	1.4375	-0.2118	5.1357	180***	-28.46***

Notes: *, ** and *** denote significance at 10%, 5% and 1% level, respectively. Pre-crisis sub-period: HK, JPN, KOA, MAL, SIG, TWN and THA begin from January 3, 1994 until July 1, 1997. Post-crisis sub-period: HK, JPN, KOA, MAL, SIG, TWN and THA begin from July 2, 1997 until December 31, 2000. Reversion sub-period: HK, JPN, KOA, MAL, SIG, TWN and THA begin from January 2, 2001 until June 30, 2004. JB represents Jarque-Bera statistics, testing for normality. ADF stands for the augmented Dickey-Fuller unit root tests. The critical values of ADF at the 10%, 5%, and 1% level are -2.57, -2.86, and -3.43, respectively.

The diagnostics of conditional variance suggests that a GARCH-class model would be appropriate. Nevertheless, ordinary GARCH models of Bollerslev (1986) do not distinguish the differential impacts of good news from bad news on volatility. To examine the asymmetric responses of volatility to positive and negative shocks, the Threshold GARCH (T-GARCH) improved by Glosten et al. (1993) is applied¹. The T-GARCH process is then defined by:

$$R_t = \mu + \phi R_{t-1} + \varepsilon_t, \quad (1)$$

$$h_t = \omega + \alpha \varepsilon_{t-1}^2 + \gamma \varepsilon_{t-1}^2 d_{t-1} + \beta h_{t-1}, \quad (2)$$

where R_t and R_{t-1} are the market return at time t and $t-1$, respectively. ε_t denotes a new market shock at time t and $\varepsilon_t \sim N(0, \sqrt{h_t})$. d_{t-1} stands for the dummy variable with a value of unity if $\varepsilon_{t-1} < 0$ and zero otherwise.

Equation (1) describes the first order autoregressive process for stock return, with ϕR_{t-1} capturing the autocorrelation. Equation (2) expresses the process of conditional variance and describes conditional variance process to respond asymmetrically to rise and fall in stock price. Specifically, positive return shocks have an impact of α , while negative return shocks have an impact of $\alpha + \gamma$. If $\gamma > 0$, it indicates the process of transitory leverage effects in the conditional variance.

The Component-GARCH (C-GARCH) model first developed by Engle and Lee (1993) is employed to decompose volatility into a short- and long-run component. Engle and Lee (1993) applied the C-GARCH model to assess the mean reversion of volatility in the US and Japanese stock markets and found the transitory component had a strong force pulling the volatility back to its permanent component². To observe whether there is any volatility change after the financial crisis resulting from the short-term or long-run behavior, we combine the C-GARCH with the T-GARCH together, which allows for asymmetric news impact. Therefore, the asymmetric C-GARCH (AC-GARCH) can be described as follows:

$$h_t = q_t + \alpha(\varepsilon_{t-1}^2 - q_{t-1}) + \gamma(\varepsilon_{t-1}^2 - q_{t-1})d_{t-1} + \beta(h_{t-1} - q_{t-1}), \quad (3)$$

$$q_t = \omega + \rho q_{t-1} + \delta(\varepsilon_{t-1}^2 - h_{t-1}). \quad (4)$$

Equation (3) expresses the process of conditional variance and allows mean reversion to a time-varying level q_t . It also describes conditional variance to react asymmetrically to return shocks, i.e., $\gamma > 0$ shows that negative return shocks will increase volatility more than positive return shocks of the equivalent magnitude. Moreover, Hadsell (2006) indicates that the volatility move halfway back to its mean following a given deviation, which is defined as $\alpha + 0.5\gamma + \beta$ in the T-GARCH model. A value less than one suggests a mean-reverting conditional volatility and shocks are transitory in nature. Equation (4) describes the permanent component of variance, q_t , which converges to ω with the speed of ρ . If $1 > \rho > \alpha + 0.5\gamma + \beta$, q_t represents the component of variance with the longest persistence, i.e., the permanent volatility will dominate the conditional variance. Note that the AC-GARCH model reduces to the T-GARCH if either $\alpha = \beta = 0$, or $\rho = \delta = 0$.

2. Empirical results

Table 2 lists the estimation results by applying the T-GARCH model to the three sub-periods. In all markets, $\phi > 0$, and is statistically significant at the 5% level except for Japan and Taiwan in the pre-crisis period. Although the coefficients of ϕ is insignificant in Japan and Taiwan, its sign is consistent with other markets. The result of post-crisis and reversion sub-periods also shows that ϕ is positive. Estimation results of $\phi > 0$ indicate the positive first order serial correlation. This result suggests a nonsynchronous trading exists in all markets. The conditional variance shows that the GARCH terms are highly statistically significant in all markets for the three sub-periods and similar to those findings in prior applications to financial data. The asymmetric volatility is captured by $\gamma > 0$ and the asymmetric response of volatility to return shocks holds in each market, i.e., negative return shocks tend to influence future volatility more than positive return shocks do. Relative to pre-crisis and reversion sub-periods, all the γ are higher during the post-crisis period except for Thailand, showing that investors are more sensitive to past negative return shocks during the post-crisis period. The volatility persistence measure of $\alpha + 0.5\gamma + \beta$ ranges from 0.855 in Singapore to 0.980 in Malaysia for the pre-crisis sub-period and from 0.910 in Singapore to 0.997 in Malaysia for the post-crisis sub-period and 0.879 in Taiwan to 0.975 in South Korea for the reversion sub-period. This result further presents that in the post-crisis period exists larger total volatility. Furthermore, all $\alpha + 0.5\gamma + \beta$ is less than one in each market for the three sub-periods, exhibiting that shocks are largely transitory.

¹ Nelson (1991) also used exponential GARCH (E-GARCH) model to distinguish the effects of good and bad news. However, E-GARCH model cannot decompose volatility into a short- and long-run component. Therefore, the T-GARCH model in this study is adopted.

² Ané (2006) agreed the ability of the C-GARCH model to capture the standard features of stock return volatility and significantly improves the goodness-of-fit. Furthermore, Gallagher (1999) and Hughes and Winters (2005) also exhibited the presence of temporary and permanent components in stock prices.

Diagnostic tests for model appropriateness are performed on the standardized and squared standardized residuals via Ljung-Box tests. We also utilize the sign bias, negative size bias, positive size bias, and joint tests to capture the robustness of the asymmetric volatility effect, all of which are proposed by Engle and Ng (1993) and the relevant supporting statistics are listed in the bottom panel of Table 2 (see Appendix).

In order to examine whether the short- and long-run volatility have changed after the Asian financial crisis, Table 3 illustrates the estimates of the AC-GARCH model for the three periods. In each market γ is positive for the three periods, meaning that the transitory asymmetric volatility exists in the pre-, post-crisis and reversion sub-periods. Similar to the results of T-GARCH model, all the γ are higher during the post-crisis period except for Thailand. Moreover, the values of $\alpha + 0.5\gamma + \beta$ is larger in the post-crisis period except for Japan. In these six markets, the average values of $\alpha + 0.5\gamma + \beta$ is 0.793 in the pre-crisis period and 0.918 in the post-crisis period and 0.808 in the reversion period. This result is similar to that of Shively (2007), i.e., the transitory volatility resulting from negative shocks is larger in the high volatility regime than in the low-volatility regime. Moreover, since the transitory volatility in the reversion period returns to the level in the pre-crisis period, the outcome demonstrates that the higher volatility after the financial crisis is a short-run phenomenon.

Normally, a high value of ρ means the permanent volatility is more persistent by nature. It can readily be observed that all the figures of ρ are larger in the post-crisis period than other two sub-periods. For instance, the average values of ρ is 0.979 for the pre-crisis sub-period, and the value is 0.985 for the post-crisis sub-period, while it is 0.947 for the reversion sub-period. This suggests that in the post-crisis period stock markets are lightly increasing volatile and increasing asymmetric, i.e., although a higher long-run volatility after the Asian financial is found, the financial turmoil does not obviously change its volatility trend. The only exception is Japan, with its coefficient of ρ much smaller in the post-crisis sub-period. Furthermore, the values of ρ are larger than $\alpha + 0.5\gamma + \beta$ in three sub-periods. This result shows that even though the permanent component of volatility has slightly changed after the Asian financial crisis, the permanent volatility still dominates the conditional variance.

According to AC-GARCH model, $\alpha + 0.5\gamma + \beta$ (ρ) measures the varying transitory (permanent) volatility. The empirical results exhibit that the values of $\alpha + 0.5\gamma + \beta$ (ρ) are larger in the post-crisis sub-period except for Japan. Furthermore, the

increment of $\alpha + 0.5\gamma + \beta$ ranges from 0.019 in Hong Kong to 0.363 in Thailand, while the increment of ρ is from 0.003 in Singapore to 0.027 in South Korea for these six markets, i.e., the increment of $\alpha + 0.5\gamma + \beta$ is higher than the increment of ρ for the post-crisis sub-period. Clearly, a higher volatility following the Asian financial crisis is due primarily to short-run but not to long-run volatility increase. Pang (2000) indicated that a sharp decline of stock returns in Thailand before the Asian financial crisis could be the reason why the transitory asymmetry in volatility is not that significant in the post-crisis sub-period. For instance, the SET index of the Thai stock market fell from its top of 1753 on January 4, 1994 to 527 on June 30, 1997, causing investors to lose about 70 percent of their portfolio value before the financial crisis. The slower speed of mean reversion in Japan before the crisis may be the results of domestic asset bubbles emergence. However, the crisis did not seem to be too much affected (see Gong et al., 2004).

Shively (2007) and others indicated that asymmetric transitory volatility was higher in the negative-return high-volatility regime than in the positive-return regime. The reason why investors react much more strongly to past negative return shocks is their wealth has shrunk markedly. Supporting prior findings, we further decompose volatility into transitory and permanent components and the empirical findings exhibit that stock market volatility increases after investors have suffered losses, with this effect being displayed in relation to both transitory and permanent components of volatility. In essence, both a higher degree of transitory and permanent volatility after the Asian financial crisis has been detected. Moreover, the effect of short-run volatility increase is larger than that of long-run volatility after the Asian financial crisis, exhibiting that the higher volatility following the Asian financial crisis is primarily attributable to short-run volatility increase.

Conclusions and implications

Different from previous research, this study tests both the short- and long-run volatility in Asian stock markets using the AC-GARCH model. The empirical results not only support the asymmetric volatility hypothesis but also detect an increasing sensitivity to bad news in both transitory and permanent volatility, especially the transitory part, which is consistent with which is consistent with Schwert's (1990) market crash study. This means that the government should not overly intervene market turbulence because the volatility reverts to its normal level quickly after the crash. And investors have to emphasize stocks fundamental sides in lieu of short-run volatility.

Despite achieving the major objectives of this investigation, numerous issues remain unsolved and warrant future research. For instance, future study could examine whether the transitory and permanent

component of volatility also exists in conditional betas. It is hoped that the findings of this study can stimulate further research and shed more lights on the stock behaviors in emerging markets.

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Appendix

Table 2. Maximum likelihood estimates of T-GARCH model for the pre-, post-crisis and reversion sub-periods

$$R_t = \mu + \phi R_{t-1} + \varepsilon_t, \quad h_t = \omega + \alpha \varepsilon_{t-1}^2 + \gamma \varepsilon_{t-1}^2 d_{t-1} + \beta h_{t-1}.$$

	Pre-crisis sub-period							Post-crisis sub-period							Reversion sub-period						
	HK	JPN	KOA	MAL	SIG	TWN	THA	HK	JPN	KOA	MAL	SIG	TWN	THA	HK	JPN	KOA	MAL	SIG	TWN	THA
μ	0.050 (0.039)	-0.019 (0.026)	-0.027 (0.037)	-0.012 (0.032)	-0.027 (0.028)	0.051 (0.046)	-0.119*** (0.039)	-0.020 (0.065)	-0.040 (0.041)	-0.080 (0.075)	-0.072 (0.061)	-0.034 (0.048)	-0.074 (0.055)	-0.247*** (0.064)	-0.015 (0.040)	-0.003 (0.041)	0.067 (0.052)	0.009 (0.025)	0.017 (0.040)	0.028 (0.052)	0.096** (0.043)
ϕ	0.076** (0.038)	0.046 (0.033)	0.107*** (0.037)	0.137*** (0.035)	0.207*** (0.037)	0.025 (0.038)	0.127*** (0.031)	0.088** (0.036)	0.089** (0.036)	0.078** (0.032)	0.143*** (0.035)	0.163*** (0.034)	0.047 (0.034)	0.085** (0.033)	0.050 (0.037)	0.060* (0.036)	0.011 (0.035)	0.126*** (0.036)	0.018 (0.039)	0.042 (0.038)	0.036 (0.035)
ω	0.050*** (0.009)	0.022** (0.010)	0.082*** (0.029)	0.022*** (0.004)	0.120*** (0.027)	0.162*** (0.030)	0.145*** (0.047)	0.189*** (0.034)	0.087*** (0.025)	0.092 (0.071)	0.083*** (0.012)	0.346*** (0.101)	0.187*** (0.036)	0.463** (0.194)	0.044*** (0.008)	0.083** (0.039)	0.075* (0.039)	0.194*** (0.060)	0.152*** (0.040)	0.062*** (0.019)	0.235** (0.098)
α	-0.001 (0.014)	0.011 (0.013)	0.020 (0.015)	0.018** (0.008)	0.091** (0.036)	0.036*** (0.013)	0.012 (0.020)	-0.007 (0.010)	0.012 (0.013)	0.033 (0.025)	0.047*** (0.011)	0.086** (0.041)	-0.015* (0.008)	0.114*** (0.036)	-0.037*** (0.008)	0.021 (0.018)	0.022 (0.018)	0.119** (0.054)	0.019 (0.021)	0.021* (0.011)	0.054 (0.035)
γ	0.098*** (0.019)	0.088*** (0.027)	0.069** (0.035)	0.077*** (0.019)	0.147*** (0.040)	0.058*** (0.019)	0.204*** (0.063)	0.155*** (0.025)	0.106*** (0.026)	0.077** (0.036)	0.120*** (0.021)	0.232*** (0.078)	0.181*** (0.026)	0.061 (0.058)	0.094*** (0.013)	0.086** (0.034)	0.058** (0.023)	0.075 (0.091)	0.154*** (0.032)	0.082*** (0.021)	0.099** (0.049)
β	0.918*** (0.013)	0.924*** (0.023)	0.872*** (0.033)	0.923*** (0.011)	0.690*** (0.052)	0.851*** (0.020)	0.824*** (0.038)	0.903*** (0.016)	0.888*** (0.026)	0.911*** (0.016)	0.890*** (0.008)	0.708*** (0.053)	0.870*** (0.018)	0.800*** (0.052)	0.942*** (0.010)	0.889*** (0.037)	0.924*** (0.024)	0.758*** (0.105)	0.802*** (0.040)	0.817*** (0.016)	0.779*** (0.069)
Log L	-1483	-1157	-1405	-1319	-1153	-1584	-1526	-1952	-1517	-2200	-1925	-1728	-1772	-1985	-1490	-1518	-1804	-1100	-1415	-1732	-1569
$\alpha + 0.5\gamma + \beta$	0.966	0.979	0.927	0.980	0.855	0.916	0.938	0.974	0.953	0.983	0.997	0.910	0.946	0.945	0.952	0.953	0.975	0.915	0.898	0.879	0.883
Diagnostics for T-GARCH model																					
LB(12)	13.432	15.392	8.456	10.310	11.548	16.370	14.981	8.772	19.160*	7.439	14.428	6.481	14.462	26.734***	10.338	4.952	8.808	12.032	8.307	8.288	13.023
LB ² (12)	4.293	17.664	14.779	10.463	5.046	9.627	10.619	8.387	16.351	10.463	3.478	2.992	11.672	20.276*	11.825	28.510***	4.129	12.299	2.896	10.891	9.349
Sign bias	0.187	0.244	-0.387	0.592	0.636	1.549	-0.791	1.024	1.475	0.592	-1.352	-0.892	-0.526	-2.078***	0.454	1.754*	2.346**	-0.625	-1.339	-1.207	0.560
Negative size	0.455	-1.035	0.991	-0.071	-0.357	0.443	0.322	-1.577	-0.022	-0.071	0.616	0.692	-0.117	2.032**	1.396	1.028	-0.159	0.224	1.506	2.042**	1.072
Positive size	-0.291	0.807	-0.015	-0.292	-0.591	-1.839*	0.452	-1.455	-1.295	-0.292	1.238	-0.440	-0.646	1.278	-0.669	-1.583	-1.681	-0.510	0.363	-1.150	-1.033
Joint test	0.172	0.871	0.394	0.918	0.156	1.928	0.218	1.216	1.198	0.918	0.762	0.689	0.644	1.713	1.563	3.689***	2.511**	0.539	0.996	3.571**	1.320

Notes: *, ** and *** denote significance at 10%, 5% and 1% level, respectively. Numbers in parentheses are standard errors. LB(12) and LB²(12) are the Ljung-Box test statistics testing for autocorrelation in the standardized residuals and standardized squared residuals of T-GARCH model up to the twelfth lags. The regressions for the asymmetric volatility tests are as follow: (1) Sign bias test: $Z_i^2 = a + bS_i + e_i$; (2) Negative size bias test: $Z_i^2 = a + bS_i\varepsilon_{i-1} + e_i$; (3) Positive size bias test: $Z_i^2 = a + b(1-S_i)\varepsilon_{i-1} + e_i$; (4) Joint test: $Z_i^2 = a + b_1S_i + b_2S_i\varepsilon_{i-1} + b_3(1-S_i)\varepsilon_{i-1} + e_i$, where z_i^2 is squared standardized residuals and S_i is a dummy that takes the value of unity if $\varepsilon_i < 0$ and zero otherwise. Asymmetric volatility tests are t -tests for coefficient b in (1), (2), and (3). The joint test is an F -test for regression (4).

Table 3. Maximum likelihood estimates of AC-GARCH model for the pre-, post-crisis and reversion sub-periods

$$R_t = \mu + \phi R_{t-1} + \varepsilon_t, \quad h_t = q_t + \alpha(\varepsilon_{t-1}^2 - q_{t-1}) + \gamma(\varepsilon_{t-1}^2 - q_{t-1})d_{t-1} + \beta(h_{t-1} - q_{t-1}), \quad q_t = \omega + \rho q_{t-1} + \delta(\varepsilon_{t-1}^2 - h_{t-1}).$$

	Pre-crisis sub-period							Post-crisis sub-period							Reversion sub-period						
	HK	JPN	KOA	MAL	SIG	TWN	THA	HK	JPN	KOA	MAL	SIG	TWN	THA	HK	JPN	KOA	MAL	SIG	TWN	THA
μ	0.006 (0.032)	-0.013 (0.024)	-0.02 (0.036)	-0.003 (0.029)	-0.007 (0.025)	0.086** (0.041)	-0.110*** (0.040)	0.086 (0.059)	-0.009 (0.038)	-0.125*** (0.008)	-0.120** (0.049)	0.000 (0.047)	-0.033 (0.046)	-0.244*** (0.065)	-0.003 (0.038)	-0.059 (0.047)	0.038 (0.062)	0.015 (0.023)	-0.004 (0.034)	0.028 (0.025)	0.116*** (0.044)
ϕ	0.007 (0.028)	0.04 (0.029)	0.112*** (0.006)	0.116*** (0.033)	0.164*** (0.033)	-0.039 (0.036)	0.134*** (0.035)	0.064* (0.034)	0.091*** (0.027)	0.083** (0.034)	0.140*** (0.031)	0.142*** (0.035)	0.037 (0.032)	0.082** (0.035)	0.051* (0.030)	0.056 (0.034)	0.032** (0.016)	0.101*** (0.034)	0.029 (0.034)	0.038 (0.029)	0.049 (0.034)
α	-0.070* (0.040)	0.036 (0.041)	0.013 (0.078)	-0.012 (0.043)	0.123 (0.083)	0.037 (0.031)	0.078 (0.070)	-0.027* (0.014)	-0.051 (0.035)	-0.030* (0.018)	0.099** (0.040)	0.052** (0.022)	-0.086*** (0.030)	0.058 (0.053)	-0.050 (0.072)	-0.135 (0.177)	0.016 (0.018)	0.200* (0.107)	-0.037 (0.094)	-0.018 (0.022)	-0.146* (0.088)
γ	0.092** (0.041)	0.068*** (0.016)	0.069 (0.047)	0.089 (0.071)	0.081 (0.082)	0.056 (0.042)	0.127 (0.088)	0.136*** (0.020)	0.077* (0.047)	0.101*** (0.022)	0.149*** (0.052)	0.153*** (0.035)	0.196*** (0.029)	0.100 (0.060)	0.071* (0.040)	0.057 (0.047)	0.022 (0.022)	0.075 (0.093)	0.098* (0.050)	0.033** (0.016)	0.080* (0.048)
β	0.949*** (0.054)	0.912*** (0.042)	0.869*** (0.135)	0.748*** (0.232)	0.652*** (0.137)	0.715*** (0.133)	0.398* (0.228)	0.903*** (0.016)	0.733*** (0.282)	0.955*** (0.021)	0.689*** (0.066)	0.762*** (0.026)	0.921*** (0.039)	0.795*** (0.088)	0.937*** (0.163)	0.933*** (0.259)	0.903*** (0.061)	0.515*** (0.160)	0.877*** (0.122)	0.790*** (0.011)	0.671* (0.362)
ω	0.023*** (0.005)	0.013*** (0.003)	0.050*** (0.009)	0.0180*** (0.005)	0.021*** (0.006)	0.028*** (0.004)	0.048*** (0.014)	0.039*** (0.005)	0.082*** (0.008)	0.035*** (0.013)	0.013*** (0.006)	0.043*** (0.004)	0.027*** (0.002)	0.105*** (0.040)	0.078*** (0.011)	0.147*** (0.015)	0.066 (0.048)	0.030 (0.025)	0.062*** (0.011)	0.053*** (0.016)	0.248*** (0.018)
ρ	0.984*** (0.011)	0.981*** (0.011)	0.970*** (0.031)	0.980*** (0.008)	0.982*** (0.012)	0.980*** (0.016)	0.974*** (0.012)	0.991*** (0.005)	0.953*** (0.019)	0.997*** (0.003)	0.994*** (0.004)	0.985*** (0.007)	0.991*** (0.040)	0.985*** (0.013)	0.980*** (0.031)	0.911*** (0.045)	0.977*** (0.011)	0.988*** (0.021)	0.954*** (0.044)	0.981*** (0.010)	0.870*** (0.055)
δ	0.045* (0.025)	-0.034 (0.038)	0.057 (0.072)	0.052** (0.018)	0.016 (0.027)	0.02 (0.014)	0.040* (0.021)	0.007 (0.005)	0.068*** (0.023)	0.023** (0.011)	0.007 (0.005)	0.009 (0.007)	0.064* (0.033)	0.053 (0.039)	0.090 (0.073)	0.136 (0.183)	0.004 (0.007)	0.035 (0.042)	0.064 (0.085)	0.059* (0.023)	0.138 (0.084)
Log L	-1455	-1494	-1609	-1297	-1146	-1540	-1531	-1960	-1523	-2199	-1860	-1777	-1774	-1985	-1486	-1519	-1842	-1108	-1384	-1742	-1584
$\alpha + 0.5\gamma + \beta$	0.925	0.982	0.917	0.781	0.816	0.780	0.540	0.944	0.721	0.975	0.863	0.891	0.933	0.903	0.923	0.827	0.930	0.753	0.889	0.789	0.565
Diagnostics for AC-GARCH model																					
LB(12)	16.559	15.837	7.884	10.235	13.248	15.631	17.209	9.409	19.810*	8.623	11.181	8.067	13.841	28.093***	11.058	4.403	9.138	16.474	8.450	8.115	13.635
LB ² (12)	3.657	12.111	17.533	2.641	8.311	8.456	7.235	6.614	12.300	8.418	2.724	3.742	16.960	19.303*	5.009	24.852**	3.941	15.165	3.682	13.109	10.825
Sign bias	0.580	1.215	1.263	0.344	1.866*	2.102**	0.544	2.310**	1.882*	1.010	-0.786	0.454	1.134	-1.364	0.481	1.914*	2.387**	0.628	-0.863	-0.504	1.103
Negative size	-0.549	-1.630	-0.925	-0.309	-1.369	0.589	-0.408	-2.544**	-0.726	-0.212	0.688	-0.441	-0.940	1.880*	0.521	0.405	-0.764	-1.154	0.744	1.516	-0.431
Positive size	-0.492	0.166	-1.501	-1.022	-1.413	-2.190**	-1.113	-1.762*	-1.585	-0.570	0.164	-0.812	-1.474	0.659	-0.039	-1.590	-1.625	-1.359	-0.393	-1.612	-0.709
Joint test	0.150	1.262	0.846	0.376	1.235	3.162**	0.423	2.655**	1.366	0.445	0.266	0.234	0.797	1.189	0.433	2.712**	2.081	0.944	0.728	3.028**	0.424

Notes: *, ** and *** denote significance at 10%, 5% and 1% level, respectively. Numbers in parentheses are standard errors. LB(12) and LB²(12) are the Ljung-Box test statistics testing for autocorrelation in the standardized residuals and standardized squared residuals of AC-GARCH model up to the twelfth lags. The regressions for the asymmetric volatility tests are as follow: (1) Sign bias test: $Z_t^2 = a + bS_t + e_t$; (2) Negative size bias test: $Z_t^2 = a + bS_t\varepsilon_{t-1} + e_t$; (3) Positive size bias test: $Z_t^2 = a + b(1 - S_t)\varepsilon_{t-1} + e_t$; (4) Joint test: $Z_t^2 = a + b_1S_t + b_2S_t\varepsilon_{t-1} + b_3(1 - S_t)\varepsilon_{t-1} + e_t$, where z_t^2 is squared standardized residuals and S_t is a dummy that takes the value of unity if $\varepsilon_t < 0$ and zero otherwise. Asymmetric volatility tests are t -tests for coefficient b in (1), (2), and (3). The joint test is an F -test for regression (4).