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Empirical Analysis of Stock Returns and Volatility: Evidence from Seven Asian Stock Markets Based on TAR-GARCH Model

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Abstract. This paper investigates the time-series behavior of stock returns for seven Asian stock markets. In most cases, higher average returns appear to be associated with a higher level of volatility. Testing the relationship between stock returns and unexpected volatility, the evidence shows that four out of seven Asian stock markets have significant results. Further analyzing the relationship between stock returns and time-varying volatility by using Threshold Autoregressive GARCH(1,1)-in-mean specification indicates that the null hypothesis of no asymmetric effect on the conditional volatility is rejected for the daily data. However, the null cannot be rejected for the monthly data.

Key words: stock returns, volatility, Asian stock markets, asymmetric effect, TAR-GARCH model

JEL Classification: G12, G15

1. Introduction

Since the events of the stock market crash in October 1992 and the Asian crisis in July 1997, a considerable amount of research has been devoted to the investigation of the sensitivity of stock returns toward risk and to the covariance of stock returns across different markets. The accumulated empirical evidence suggests that, in addition to the traditional economic forces (Chen et al., 1986), stock returns have been analyzed typically by employing time-series models. The research may be categorized into two approaches: (i) investigation of time-series patterns and cross correlations of stock returns and (ii) examination of the relationship between stock returns and conditional variance. The main concern of the first approach is to detect whether there is a predictable pattern associated with stock-return series. A predicable pattern implies a profitable trading rule, rejecting an efficient-market hypothesis. The evidence reported by Fama and French (1988), Poterba and Summers (1988), and Ding et al. (1993) suggests that there is a long memory or mean reversion in stock returns. These studies conclude that not all of the time series of stock returns follow a random-walk process. In cross-country studies, findings provided by Kim and Rogers (1995), Koutmos and Booth (1995), Wei et al. (1995), and Chiang and Jiang (1998) indicate that national stock returns are significantly correlated; and the linkages among international stock markets have grown more interdependent over time.

The second approach of studying stock series is to link the stock returns to risk factors. It has been observed that stock volatility exhibits a clustering phenomenon, i.e., large changes tend to be followed by large changes and small changes tend to be followed by small changes. In modeling this market phenomenon, Autoregressive Conditional Heteroscedasticity (ARCH) and the extension to the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model (Bollerslev, 1986) have been employed.[1] As reported by Bollerslev et al. (1992), the GARCH(1,1) model appears to be sufficient to describe the volatility evolution of stock-return series. Due to the fact that the GARCH model fails to take into account the asymmetric effect between positive and negative stock returns, the weighted innovation models such as exponential GARCH (Nelson, 1991) and Threshold Autoregressive GARCH or TAR-GARCH model (Glosten et al., 1993, henceforth, GJR; Engle and Ng, 1993; Tsay, 1998) have been advanced. This line of research highlights the asymmetric effect by emphasizing that a negative shock to returns will generate more volatility than a positive shock of equal magnitude.

Despite a substantial amount of empirical research on stock-market behavior, most studies have concentrated on the major developed stock markets. There have been only a few comparable research works devoted to investigation of Asian Stock Markets.[2] For this reason, we examine time-series behavior of seven Asian stock markets, including Hong Kong, Malaysia, the Philippines, Singapore, South Korea, Thailand, and Taiwan. Particular attention is given to the empirical relationship between stock returns and volatility by employing a TAR-GARCH specification.

Our research interest in Asian markets is further motivated by recent developments in market phenomena. First, Asian stock markets, with the exceptions of Japan, Hong Kong and Singapore, have experienced a rapid growth in gross national product, contributing to a significant rise in savings and, hence, in the supply of loanable funds. An increase in demand for international financial assets has resulted. Second, since deregulation of the financial industry in most Asian countries in recent years, stock prices and capital movements are sensitive to news, return differentials, technological innovations, changes in business conditions, and political events in domestic market as well as in external sources. As a result, the volatile behavior of asset returns interacts dynamically with shocks in the rest of world through a contagion effect or other channels of transmission. Thus, the issue of volatility is not only a regional phenomenon, but also an integral part of global risk analysis. To provide more accurate information to aid global portfolio managers in achieving an efficient mean-variance frontier and to provide policy-makers with a more definite basis on which to formulate appropriate risk-management strategy, it is of interest to conduct an empirical investigation on stock-return reaction to risk.

This paper extends the existing research (Choudhry, 1996; De Santis and Imrohoroglu, 1997; Chiang and Jiang, 1998) in several ways. First, we use more recent daily data, starting from the post-crash period of 1987 and focus on seven Asian markets. Second, in addition to examining the relationship between stock returns and the predicted/unpredicted volatility (French et al., 1987), asymmetries in the time-varying volatility process are investigated. Third, both low-frequency and high-frequency data are used to examine the test equations. This allows us to discriminate performance with respect to different data frequencies. Finally, to check the empirical findings, diagnostic methods proposed by Engle and Ng (1993) are employed to assess the robustness of the model.

This paper is organized into following sections. Section 2 describes the data used in this study and presents some statistical properties of stock returns with different frequencies of the data. Section 3 provides the measures of observed and predicted volatility for each Asian stock market and examines stock returns and expected/unexpected standard deviations. Section 4 investigates the relationship between stock returns and volatility based on a Threshold Autoregressive GARCH(1,1)-in-mean model. Section 5 contains concluding remarks.

2. The data and basic statistics

2.1. Data sample

The data used in this study are the daily stock-price indexes for seven Asian stock markets from January 1988 through June 1998.[3] The data consist of the Hang Seng Index (Hong Kong), the Kuala Lumpur Composite Price Index (Malaysia), the Manila SE Composite Price Index (the Philippines), the Straits Times Industrial Index (Singapore), the Korea Composite Price Index (South Korea), the Stock Exchange of Thailand Daily Index (Thailand), the Taiwan Stock Exchange Weighted Stock Index (Taiwan), the Nikkei 225 Index (Japan), and the S&P 500 Index (United States).[4] U.S. and Japan stock returns are included for comparison with the major developed markets. Daily stock returns are obtained by taking the logarithmic difference of the daily stock index times 100. That is, $R_t = 100 * (\log P_t, - \log P_{t-1})$. To avoid a possible weekend effect, weekly indexes are derived by utilizing closing prices quoted on Thursday. If Thursday price data are not available, then Wednesday's closing prices are used. With respect to monthly data, the stock indexes are measured by the last trading day of each month.

2.2. Basic statistics

To provide a general understanding of the nature of each market return and to compare the distinctive properties across countries in Asia, we present summary statistics of daily, weekly, and monthly returns in Tables 1, 2, and 3, respectively. The statistics include mean return, standard deviation, skewness, excess kurtosis, autocorrelation, and Ljung-Box $Q(12)$ value for the returns and squared returns.

Under different measures of frequency, Hong Kong has the highest mean among the seven Asian stock markets, followed by Taiwan, while Korea has the lowest one. However, the U.S. stock market has performed even better than Hong Kong has over the last decade. In

Table 1. Sample statistics of daily market returns: 1/4/1988–6/30/1998 (2738 observations)

	HK	KR	MA	PH	SG	TW	TH	JP	US
Mean	0.00048	−0.00020	0.00020	0.00028	0.00009	0.00043	−0.00003	−0.00011	0.00054
Std. Dev.	0.0165	0.0165	0.0144	0.0171	0.0115	0.0213	0.0171	0.0136	0.0082
Skewness	−1.37**	0.14**	1.07**	−0.02	−0.15**	−0.10*	0.10*	0.35**	−0.51**
Kurtosis	30.05**	5.71**	24.83**	18.29**	16.49**	2.76**	5.99**	5.77**	7.02**
ACF									
ρ_1	0.0018	0.0544**	0.1560**	0.1246**	0.1677**	0.0681**	0.1524**	−0.0022	0.0042
ρ_2	−0.0337	0.0068	0.0360	0.0253	0.0441*	0.0658**	0.0124	−0.0656**	−0.0216
ρ_3	0.1082**	−0.0334	−0.0217	0.0044	0.0155	0.0414*	0.0319	0.0003	−0.0580**
ρ_4	−0.0188	−0.0290	−0.0155	0.0311	−0.0118	0.0032	0.0272	0.0243	−0.0150
ρ_5	−0.0501**	−0.0193	−0.0213	0.0085	−0.0417*	−0.0091	0.0153	−0.0254	−0.0143
ρ_6	−0.0132	−0.0320	−0.0352	−0.0446*	−0.0090	0.0054	−0.0332	−0.0116	−0.0299
ρ_9	−0.0074	0.0204	0.0170	0.0261	0.0120	−0.0045	0.0473*	0.0515**	0.0268
ρ_{12}	0.0034	−0.0289	−0.0002	0.0758**	0.0355	0.0506**	0.0063	0.0008	0.0311
$Q(12)$	60.36**	29.28**	88.66**	73.16**	111.58**	54.96**	87.38**	27.59**	30.94**
$Q^2(12)$	348**	1402**	276**	489**	664**	2068**	1084**	437**	137**

Notes: HK = Hong Kong, KR = Korea, MA = Malaysia, PH = Philippines, SG = Singapore, TW = Taiwan, TH = Thailand, JP = Japan, US = United States.

$Q(12)$ is the Ljung-Box Q-statistic that tests the joint significance of the autocorrelations of the daily return series up to the 12th order. $Q^2(12)$ is the Ljung-Box Q-statistic that tests the joint significance of the autocorrelations of the squared daily-return series up to the 12th order. The critical value is 26.2, and 21.0 for the 1% and 5% levels, respectively.

* and ** indicate statistically significant at 5% and 1% levels, respectively.

Table 2. Sample statistics of weekly market returns: 1/4/1988–6/30/1998 (547 observations)

	HK	KR	MA	PH	SG	TW	TH	JP	US
Mean	0.0024	−0.0010	0.0010	0.0014	0.0005	0.0022	−0.0002	−0.0006	0.0027
Std. Dev.	0.0371	0.0364	0.0364	0.0171	0.0286	0.0532	0.0431	0.0291	0.0170
Skewness	−1.52**	−0.08	−0.76**	−0.62**	−0.53**	−0.44**	−0.62**	−0.33**	−0.35**
Kurtosis	7.79**	5.03**	8.59**	3.77**	8.05**	2.72**	4.82**	3.01**	1.22**
ACF									
ρ_1	0.0106	−0.0358	−0.0371	0.0742	0.0203	0.0149	0.0674	−0.0422	−0.0857*
ρ_2	0.1170	0.1257**	−0.0159	0.0699	0.0773	0.1729**	0.0754	0.0935*	0.0440
ρ_3	−0.0523	0.0532	0.0648	0.0469	0.0432	0.0067	0.0511	0.0526	−0.0110
ρ_4	−0.0588	0.0555	0.0301	−0.0634	−0.0469	0.0168	0.0967*	−0.0595	−0.0380
ρ_5	−0.0480	−0.0280	0.0250	0.0712	−0.0375	0.0213	0.0153	0.0026	−0.0631
ρ_6	−0.0457	0.0547	−0.0425	0.0343	0.0696	0.0207	0.0872*	−0.0186	0.0014
ρ_9	0.0770	−0.0527	−0.0450	−0.0919*	−0.0411	−0.0223	−0.0031	0.0119	0.0436
ρ_{12}	−0.0002	−0.0208	0.0329	−0.0395	−0.0017	0.0154	−0.0269	−0.0604	−0.0510
$Q(12)$	20.06	34.28**	27.85**	29.16**	14.86	19.51	20.57	14.70	16.30
$Q^2(12)$	37**	280**	179**	49**	95**	506**	120**	120**	48**

Notes: HK = Hong Kong, KR = Korea, MA = Malaysia, PH = Philippines, SG = Singapore, TW = Taiwan, TH = Thailand, JP = Japan, US = United States.

$Q(12)$ is the Ljung-Box Q-statistic that tests the joint significance of the autocorrelations of the weekly return series up to the 12th order. $Q^2(12)$ is the Ljung-Box Q-statistic that tests the joint significance of the autocorrelations of the squared weekly-return series up to the 12th order. The critical value is 26.2, and 21.0 for the 1% and 5% levels, respectively.

* and ** indicate statistically significant at 5% and 1% levels, respectively.

Table 3. Sample statistics of monthly market returns: 1/4/1988–6/30/1998 (126 observations)

	HK	KR	MA	PH	SG	TW	TH	JP	US
Mean	0.0105	−0.0044	0.0044	0.0061	0.0021	0.0093	−0.0006	−0.0023	0.0118
Std. Dev.	0.0805	0.0874	0.0790	0.0948	0.0664	0.1243	0.1031	0.0677	0.0344
Skewness	−0.58**	0.49*	−0.28	−0.24	−0.46*	−0.39	−0.18	−0.27	−0.23
Kurtosis	3.23**	3.99**	1.69**	1.44**	2.60**	1.53**	0.82	0.75	0.45
ACF									
ρ_1	−0.0671	0.0715	0.0355	0.0862	0.0089	0.1383	0.1583	−0.0290	−0.1574
ρ_2	0.0484	0.0295	0.2050*	0.0192	0.0567	0.0127	0.1184	−0.0389	0.0587
ρ_3	−0.0297	−0.2052*	−0.1069	−0.0154	0.0128	0.0356	−0.0537	−0.0083	−0.0157
ρ_4	−0.1666	−0.0736	−0.1240	0.0202	−0.0717	0.0582	−0.0936	−0.0216	−0.0727
ρ_5	−0.0542	0.0284	0.0371	−0.0453	0.0300	−0.0767	−0.1415	0.1088	−0.0060
ρ_6	−0.1186	0.0897	−0.0589	−0.2004*	−0.0085	−0.0562	0.0058	−0.1052	−0.1309
ρ_9	0.1135	0.1668	0.0604	0.0046	0.0607	0.0883	0.0256	0.0229	0.0048
ρ_{12}	−0.0633	−0.0129	0.0626	0.0131	0.1209	−0.0787	0.0775	−0.0493	−0.1045
$Q(12)$	22.81*	14.30	19.63	10.83	5.42	8.31	22.48*	4.53	13.60
$Q^2(12)$	8.51	22.31*	46.54**	15.01	58.38**	46.15**	23.79*	26.62**	25.47*

Notes: *HK = Hong Kong, KR = Korea, MA = Malaysia, PH = Philippines, SG = Singapore, TW = Taiwan, TH = Thailand, JP = Japan, US = United States.*

$Q(12)$ is the Ljung-Box Q-statistic that tests the joint significance of the autocorrelations of the monthly return series up to the 12th order. $Q^2(12)$ is the Ljung-Box Q-statistic that tests the joint significance of the autocorrelations of the squared monthly-return series up to the 12th order. The critical value is 26.2, and 21.0 for the 1% and 5% levels, respectively.

* and ** indicate statistically significant at 5% and 1% levels, respectively.

general, the Asian stock markets are characterized by a higher volatility than that observed in developed markets such as the United States and Japan. Taiwan appears to be the most volatile market, while Singapore is the most stable one. In most cases, higher average returns appear to match higher volatility.

Another characteristic of the stock-return series is a high value of kurtosis, especially in the high frequency data shown in Tables 1 and 2. This suggests that, for these markets, big shocks of either sign are more likely to be present and that the stock-return series may not be normally distributed. The independence of the stock returns is also challenged as seen in the rejection of the absence of first-order autocorrelation for the daily data. The Ljung-Box statistics, denoted by $Q(12)$,[5] for testing the independence of the stock return series up to 12 orders, show that the null hypothesis of no dependency on stock returns is decisively rejected for all daily stock returns. However, the null is rejected in four markets in weekly-return series and reduced to two in monthly data. It can be seen that these autocorrelated return phenomena are attributable partially to the imposition of daily price limits on stock price movements in some of the Asian markets. Finally, we examine the dependency on the squared returns by using Ljung-Box statistics. The null is rejected in virtually all of cases as shown in Tables 1, 2, and 3. The evidence, however, shows the $Q^2(12)$ statistics are significantly higher for the daily data; the values decline as the frequency of the data moves to a weekly and then a monthly basis. This suggests that the dependency of volatility is more noticeable in the higher frequency data, meaning that a GARCH specification appears to be more appropriate for modeling the daily and weekly returns.

3. The relationship between returns and volatilities

French et al. (1987) provide a direct test of the relationship between excess returns and volatility. They document that market excess returns are positively related to the expected volatility of stock returns, but negatively related to the unexpected volatility of stock returns. The 1987 crash added more weight to this popular hypothesis by suggesting that a lower return than average would induce more speculative activity and therefore increase market volatility. Thus, this hypothesis suggests a negative association between expected return and unexpected volatility. However, a positive relationship between expected return and expected volatility is plausible since a higher expected return is required to compensate for risk when volatility is relatively high.

The relationship between stock returns and standard deviations for each country are tested by using:[6]

$$R_{it} = \alpha_0 + \alpha_1 \hat{\sigma}_{it}^{e} + \varepsilon_{it}, \tag{1}$$

$$R_{it} = \alpha_0 + \alpha_1 \hat{\sigma}_{it}^{u} + \varepsilon_{it} \tag{2}$$

where $\hat{\sigma}_{it}^{e}$ and $\hat{\sigma}_{it}^{u}$ are, respectively, the expected and unexpected monthly standard deviations of market returns for the ith country. The estimation of variance also follows the work of

French et al. (1987). The monthly variance of returns is calculated by the sum of the squared daily returns plus twice the sum of the products of adjacent returns.[7] The calculation is given by:

$$\sigma_{it}^2 = \sum_{j=1}^{N_t} R_{i,j,t}^2 + 2\sum_{j=1}^{N_t-1} R_{i,j,t}R_{i,j+1,t} \tag{3}$$

where there are N_t daily returns R_{jt} in month t and σ_{it}^2 provides an estimate of the variance for the ith stock index in month t. The second term of equation (3) allows for first-order autocorrelation of stock returns resulting from nonsynchronous trading (Fisher, 1966; Scholes and Williams, 1977).[8]

To reduce the volatile character of the volatility, the variance series has been transformed by taking natural logarithms. Assuming that the expected value of the standard deviation of the stock returns can be projected by using an optimal forecast scheme, the expected standard deviation is obtained by fitting the data into an ARIMA process with the use of Box and Jenkins methodology (1976):[9,10]

$$\sigma_{it} = [\theta(B)/\Phi(B)]\varepsilon_{it} \tag{4}$$

where $\Phi(B) = (1-\alpha_1 B - \alpha_2 B^2 - \cdots - \alpha_p B^p)$, $\theta(B) = (1-\theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q)$, B is the backward shift operator, and ε_{it} is white noise. The unexpected standard deviation, $\hat{\sigma}_{it}^u$, is obtained by taking the difference between the actual standard deviation and the expected standard deviation, i.e., $\hat{\sigma}_{it}^u = \sigma_{it} - \hat{\sigma}_{it}^e$.

Table 4 presents the estimates for equations (1) and (2). The statistics do not lend much support for the relationship between stock returns and expected volatility. Although the coefficients for Hong Kong and Thailand are found to be statistically significant, both of them bear a wrong sign. The data appear to be more consistent with the specification of equation (2). Specifically, the t-statistics indicate that, with the exceptions of Korea, the Philippines, and Thailand, stock market returns are explained significantly by the unexpected standard deviation and the coefficients have a negative sign. The finding of this negative relationship is consistent with evidence in United States reported by French et al. (1987).

4. A threshold autoregressive GARCH(1,1)-in-mean model

A key criticism in studying the relationship between stock returns and volatility is that this specification fails to account for time-varying risk (Merton, 1980). To address the issue of heteroscedasticity, a number of empirical studies have shown that the volatility series exhibits clustering phenomenon, i.e., large changes tend to be followed by large changes and small changes tend to be followed by small changes. As we reported in Tables 1, 2, and 3, the relatively large value of the kurtosis statistic suggests that the underlying time series is leptokurtic, or heavily tailed and sharply peaked about the mean as compared with

Table 4. Estimates of monthly returns and expected/unexpected components of standard deviations

Market		Constant	$\hat{\sigma}_{it}^{e}$	$\hat{\sigma}_{it}^{u}$	R^2	D.W.	$Q(12)$
Hong Kong	(3)	0.0655*	−0.8344*		0.0355	2.17	23.73*
		(2.35)	(2.08)				
	(4)	0.0100		−0.7762**	0.0918	2.29	24.40*
		(1.39)		(3.44)			
Korea	(3)	0.0169	−0.3408		0.0069	1.82	16.29
		(0.64)	(0.92)				
	(4)	−0.0062		−0.2047	0.0070	1.87	14.57
		(0.80)		(0.92)			
Malaysia	(3)	0.0215	−0.2825		0.0085	1.93	19.82
		(1.14)	(1.02)				
	(4)	0.0041		−0.4629*	0.0348	2.00	18.90
		(0.57)		(2.08)			
Philippine	(3)	−0.0203	0.3426		0.0042	1.81	11.09
		(0.52)	(0.72)				
	(4)	0.0068		−0.2921	0.0122	1.83	12.73
		(0.80)		(1.22)			
Singapore	(3)	−0.0025	0.0660		0.0002	1.92	4.38
		(0.11)	(0.15)				
	(4)	0.0016		−0.8687**	0.1520	1.98	7.62
		(0.29)		(4.64)			
Taiwan	(3)	0.0142	−0.0873		0.0006	1.76	10.65
		(0.46)	(0.28)				
	(4)	0.0058		−0.9593**	0.0844	1.69	16.17
		(0.55)		(3.35)			
Thailand	(3)	0.0702*	−0.9296*		0.0391	1.70	18.65
		(2.11)	(2.24)				
	(4)	−0.0014		−0.2819	0.0110	1.75	19.19
		(0.15)		(1.17)			
Japan	(3)	−0.0037	0.0094		0.0000	2.08	4.99
		(0.17)	(0.02)				
	(4)	−0.0033		−0.3587	0.0198	2.19	6.32
		(0.55)		(1.16)			
US	(3)	0.0059	0.1750		0.0011	2.31	13.18
		(0.34)	(0.36)				
	(4)	0.0120**		−0.3230	0.0125	2.33	12.49
		(3.87)		(1.24)			

Notes: The estimated equations are:

$$R_{it} = \alpha_0 + \alpha_1 \hat{\sigma}_{it}^{e} + \varepsilon_{it}$$

$$R_{it} = \alpha_0 + \alpha_1 \hat{\sigma}_{it}^{u} + \varepsilon_{it}$$

where values in parentheses are absolute t-statistics.

* and ** indicate significance at the 1% and 5% levels, respectively.

$Q(12)$ is the Ljung-Box Q-statistic that tests the joint significance of the autocorrelations of the standardized residuals up to the 12th order. The critical values are 26.2 and 21.0 for the 1% and 5% levels, respectively.

a normal distribution. Since all GARCH-type models feature this property of leptokurtosis, the variance behavior can be modeled in a more accurate way.

Recent empirical evidence indicates that the impact of news may be "asymmetric." Specifically, good news and bad news may have different impacts on predicting future volatility. This asymmetric effect on conditional variance has been investigated extensively by the studies of the Exponential GARCH (EGARCH) model (Pagan and Schwert, 1990; Nelson, 1991) and the Threshold Autoregressive GARCH (TAR-GARCH) model (GJR, 1993). The TAR-GARCH specification is attractive since fewer parameters need to be estimated. Moreover, in their study of daily stock returns in the Japanese market, Engle and Ng (1993) find that the parameterization of TAR-GARCH is the most promising one.[11]

To incorporate this feature into the investigation of the relationship between stock returns and conditional volatility for the seven Asian stock markets, the model is estimated by TAR-GARCH(1,1)-in-mean specification as follows:[12,13]

$$R_{it} = a_0 + \sum_{j=1}^{n} b_j R_{i,t-j} + \gamma h_{it}^{1/2} + \varepsilon_{it}$$
$$\varepsilon_{it}/\Omega_{t-1} \sim N(0, h_{it}) \tag{5}$$

$$h_{it} = \varpi + \beta h_{i,t-1} + (\alpha + \eta I_{t-1})\varepsilon_{i,t-1}^2 \tag{6}$$

The market return, R_{it}, is assumed to be linearly related to its autoregressive components[14] and its own conditional standard deviation $h_{it}^{1/2}$. The innovation ε_{it} is conditional on the information set Ω_{t-1} with zero mean and variance h_{it}. The influence of volatility on stock returns is captured by the estimated coefficient γ. A significant and positive coefficient on γ implies that investors will be compensated by higher returns for bearing a higher level of risk, while a significant negative coefficient implies that investors will be penalized by bearing risk.

The conditional variance in equation (6) is assumed to be predicted by the previous variance h_{t-1} and the square of the lagged shock term ε_{t-1}^2. The difference of equation (6) from the traditional GARCH(1,1) model (Bollerslev, 1986) is that the positive and negative shocks are differentiated by using an indicator variable, I_{t-1}. It takes a value of unity when the previous shock is negative and zero otherwise. This specification allows us to examine the asymmetry in volatility with respect to ε_{t-1}. A positive η implies that a negative innovation increases conditional volatility. Thus, the asymmetric effect is captured by the hypothesis that $\eta > 0$. The system of equations (5) and (6) can be viewed as a more general model since the standard GARCH(1,1)-in-mean specification can be achieved by the restriction that $\eta = 0$.

The TAR-GARCH(1,1)-in-mean is estimated jointly by employing an appropriate maximum likelihood procedure of Berndt et al. (1974), imposing restrictions $\varpi > 0, \alpha \geq 0$, and $\beta \geq 0$ to ensure that the conditional variance in equation (6) is positive. The results of estimating the TAR-GARCH(1,1)-in-mean model for the seven Asian stock markets are reported in Tables 5, 6, and 7, based on daily, weekly, and monthly return series, respectively.

Table 5. Estimates of TAR-GARCH(1,1)-in-mean model of daily stock returns

	HK	KR	MA	PH	SG	TW	TH	JP	US
A. Return equations									
a_0	0.0012	0.0013	0.0002	0.0074	0.0005	0.0006	0.0009	0.0002	−0.0006
	(1.48)	(1.59)	(0.42)	(0.58)	(0.58)	(0.57)	(1.14)	(0.41)	(0.51)
b_1	0.0469*	0.0563*	0.2382**	0.1969**	0.1974**	0.0586*	1.1616**		−0.0365*
	(2.40)	(2.39)	(10.46)	(8.77)	(9.00)	(2.50)	(7.49)		(1.98)
b_2	−0.0650**			0.0549**		0.0774**			
	(3.56)			(3.28)		(3.93)			
b_3						0.0338*			
						(1.90)			
γ	−0.0308	0.0699	0.0500	0.0471	0.0588	0.0550	−0.0591	−0.0106	0.1508
	(0.46)	(1.12)	(0.89)	(0.54)	(0.64)	(0.89)	(0.97)	(0.21)	(0.98)
lags	(3, 5)	(1)	(1)	(1, 12)	(1)	(1, 2, 12)	(1)		(3)
B. Variance equations									
ϖ	0.0000**	0.0000**	0.0000**	0.0000**	0.0000**	0.0000**	0.0000**	0.0000**	0.0000**
	(18.08)	(11.93)	(30.77)	(15.87)	(27.13)	(11.86)	(13.32)	(9.81)	(12.91)
α	0.0736**	0.1380**	0.1104**	0.1651**	0.0596**	0.0793**	0.1008**	0.0882**	0.0008
	(7.01)	(12.31)	(8.01)	(10.39)	(5.39)	(6.68)	(10.45)	(9.03)	(0.07)
β	0.7501**	0.7318**	0.7925**	0.6675**	0.7032**	0.7838**	0.7877**	0.7799**	0.5412**
	(81.21)	(59.85)	(115.54)	(38.92)	(72.49)	(67.21)	(136.32)	(88.06)	(17.16)
η	0.2187**	0.1287**	0.1155**	0.0939**	0.2085**	0.1551**	0.1531**	0.2304**	0.2637**
	(12.59)	(5.19)	(6.49)	(3.77)	(10.14)	(7.47)	(8.10)	(11.48)	(10.80)

(*Continued*)

Table 5. (*Continued*)

	HK	KR	MA	PH	SG	TW	TH	JP	US
C. Diagnostics on standardized residuals									
$Q(12)$	43.01**	10.75	8.76	8.67	17.01	19.43	27.71**	10.62	21.80*
$Q^2(12)$	12.63	33.61**	2.78	0.48	0.74	34.22**	11.73	14.68	18.90
Sign	1.17	0.26	0.25	0.73	1.41	1.16	0.70	1.13	0.29
Negative	−0.98	1.21	0.85	0.20	−0.11	1.69	0.75	1.03	1.58
Positive	−1.30	−0.76	−0.27	−0.61	−0.29	−1.81	−0.41	−2.25*	−0.51

Notes: HK = Hong Kong, KR = Korea, MA = Malaysia, PH = Philippines, SG = Singapore, TW = Taiwan, TH = Thailand, JP = Japan, US = United States.

The estimated equations are:

$$R_{it} = a_0 + \sum_{2j=1}^{n} b_j R_{i,t-j} + \gamma h_{it}^{1/2} + \varepsilon_{it}$$

$$h_{it} = \varpi + \alpha\varepsilon_{i,t-1} + \beta h_{i,t-1} + \eta\varepsilon_{i,t-1}^2 I_{t-1}$$

The values in the parentheses are the absolute t-statistics.

The order of j in the return equation for stock market i is based on the statistical significance of autocorrelation, as evident from Table 1. During the estimation process, insignificant terms are deleted. The lags in this table imply which order of autocorrelation the model chooses. For example, for the Hong Kong stock market, the mean equation consists of AR(3) and AR(5).

$Q(12)$ is the Ljung-Box Q-statistic that tests the joint significance of the autocorrelations of the standardized residuals up to the 12th order. $Q^2(12)$ is the Ljung-Box Q-statistic that tests the joint significance of the autocorrelations of the squared standardized residuals up to the 12th order. The critical values are 26.2 and 21.0 for the 1% and 5% levels, respectively.

Sign-bias test: $Z_t^2 = a + bI_{t-1} + u_t$. Negative size-bias test: $Z_t^2 = a + bI_{t-1}\varepsilon_{t-1} + u_t$. Positive size-bias test: $Z_t^2 = a + b(1 - I_{t-1})\varepsilon_{t-1} + u_t$. All test statistics refer to the t-statistics of coefficient b in the above equation.

* and ** indicate statistically significant at 5% and 1% levels, respectively.

Table 6. Estimates of TAR-GARCH(1,1)-in-mean model of weekly stock returns

	HK	KR	MA	PH	SG	TW	TH	JP	US
A. Return equations									
a_0	0.0040	−0.0031	0.0057	0.0002	0.0000	−0.0037	0.0084	−0.0025	0.0022
	(0.54)	(0.46)	(1.45)	(0.10)	(0.00)	(0.77)	(1.06)	(0.49)	(0.51)
b_1						0.1077*	1.1069**		
						(2.29)	(3.63)		
γ	−0.0327	0.0410	−0.1308	0.0276	0.0425	0.1096	−0.1915	0.0741	0.0218
	(0.14)	(0.19)	(0.93)	(0.67)	(0.26)	(0.89)	(0.90)	(0.36)	(0.02)
lags						(2)	(4)		
B. Variance equations									
ϖ	0.0004**	0.0004**	0.0001**	0.0016	0.0002**	0.0002**	0.0006**	0.0002**	0.0003**
	(9.19)	(6.17)	(6.03)	(0.91)	(5.23)	(5.11)	(7.79)	(6.01)	(0.26)
α	0.0538	0.2173**	0.3094**	0.0271	0.0501	0.3276**	0.1162**	0.0615	0.0481
	(1.04)	(4.40)	(5.25)	(0.76)	(1.11)	(4.35)	(3.31)	(1.29)	(0.61)
β	0.4285**	0.3883**	0.5844**	0.0014	0.4874**	0.6124**	0.3271**	0.5064**	0.0029
	(8.93)	(5.91)	(15.09)	(0.00)	(8.75)	(15.88)	(4.52)	(10.48)	(0.00)
η	0.4373**	0.2192	0.0741	−0.0224	0.5039**	−0.0159	0.5325**	0.4180**	0.0640
	(5.90)	(1.88)	(0.98)	(0.47)	(4.14)	(0.17)	(3.71)	(4.18)	(0.11)
C. Diagnostics on standardized residuals									
$Q(12)$	18.37	23.14*	9.06	23.17*	16.8	14.94	16.95	13.51	16.39
$Q^2(12)$	15.64	18.07	20.36	36.98**	20.15	13.35	15.26	32.84**	24.35*
Sign	0.06	−1.06	0.32	1.42	1.05	1.15	0.73	−0.13	0.81
Negative	0.95	1.46	0.84	0.65	1.16	0.18	0.50	1.90	−1.75
Positive	−0.43	1.12	−1.68	0.24	0.74	−1.42	−0.61	0.16	−0.56

Notes: (See Table 5).

Table 7. TAR-GARCH(1,1)-in-mean model of monthly stock returns

	HK	KR	MA	PH	SG	TW	TH	JP	US
A. Return equations									
a_0	0.0210	−0.0443*	0.0400*	0.1732	0.0030	0.0282	0.3054	−0.0376	−0.0267
	(0.17)	(2.22)	(2.38)	(0.40)	(0.10)	(0.46)	(0.56)	(0.72)	(0.58)
γ	−0.0898	0.5384*	−0.4296	−1.7402	−0.0852	−0.2225	−3.0794	0.541	1.0937
	(0.06)	(2.15)	(1.79)	(0.37)	(0.17)	(0.42)	(0.55)	(0.64)	(0.85)
B. Variance equations									
ϖ	0.0067**	0.0043**	0.0012*	0.0087**	0.0030**	0.0042**	0.0092**	0.0040**	0.0012**
	(5.67)	(3.58)	(2.24)	(7.65)	(7.20)	(2.66)	(6.88)	(6.41)	(5.80)
α	0.0001	0.0000	0.4619	0.0128	0.1418	0.0000	0.0624	0.0000	0.0001
	(0.00)	(0.00)	(1.95)	(0.14)	(1.18)	(0.00)	(0.64)	(0.00)	(0.00)
β	0.0342	0.0090	0.3245**	0.0000	0.0000	0.5496**	0.0000	0.0000	0.0000
	(0.40)	(0.05)	(3.57)	(0.00)	(0.00)	(4.25)	(0.00)	(0.00)	(0.01)
η	0.1692	0.9592**	0.3762	0.0798	0.3827	0.4401	0.0663	0.2822	0.2278
	(0.64)	(2.81)	(1.26)	(0.55)	(1.32)	(1.56)	(0.37)	(1.11)	(0.83)
C. Diagnostics on standardized residuals									
Q (12)	21.68*	12.71	18.33	9.81	9.98	10.61	15.73	6.88	11.93
$Q^2(12)$	7.92	4.28	14.28	12.25	10.22	10.32	14.68	9.11	15.14
Sign	−0.10	0.75	0.74	0.19	−0.85	−0.74	0.35	1.66	−0.27
Negative	−0.24	−0.04	0.32	−0.32	0.02	0.52	0.32	−0.29	0.39
Positive	−0.73	0.37	−1.65	−0.15	0.05	−0.54	0.41	−0.63	0.08

Notes: (See Table 5).

In summarizing the estimated results, we first consider the mean equation. The evidence from daily return series indicates that all of the Asian stock returns display some sort of positive serial correlation. The Taiwan market appears to have a longer lag, which may result from a limit-price policy. Obviously, the random-walk hypothesis cannot be supported by the daily data in these Asian markets. However, the results derived from weekly and monthly data indicate very little evidence to support the significance of the AR components, whereas only the coefficients on Taiwan and Thailand stock returns are significant in the weekly data. Consistent with the finding in literature, we fail to find any statistical significance by including a conditional variance term in the return equation, with the exception of Korean market returns in the monthly series. Thus, it is clear that the estimated conditional volatility is unable to predict future expected returns with any data frequency for the seven Asian stock markets.

With respect to the estimates of the variance equation, the evidence from the daily series indicates that all of the GARCH parameters are statistically significant. Since the estimated β coefficients in the conditional variance equation are considerably larger than that of α, implying that the prediction of the volatility is dominated by the AR component.

A striking result that emerges from the variance equation is that the hypothesis of no asymmetric effect ($\eta = 0$) is strongly rejected at a high level of significance. Moreover, the estimated results show that the sum of estimated coefficients in the variance equation is close to unity, meaning that the evolution of volatility occurs in a persistent fashion and that the shocks may persist over a longer period of time.

Comparing the results of the daily series (Table 5) with those of the lower frequency series in Tables 6 and 7, we find that, with the exception of the Philippines, the GARCH(1,1) specification is still valid for the weekly data although the estimated value and the significant level of the estimated coefficients are smaller. However, when the estimates are derived from monthly data, no general GARCH or TAR-GARCH effects are present. By the same token, the asymmetric effect disappears when the estimations are made by low-frequency data. Thus, whether the TAR-GARCH(1,1) is an appropriate specification to describe the conditional variance seems to depend on the frequency of the data.

Finally, we compute the Ljung-Box (LB) statistics to conduct diagnostic checking. With a few exceptions in daily and weekly data, the calculated LB values, denoted by $Q(12)$ and $Q^2(12)$, show that the null hypothesis of the absence of autocorrelation up to twelve orders cannot be rejected.[15] This suggests that some higher orders of correlation were excluded from the model. Further checking the sign-biased tests proposed by employing Engel and Ng (1993)[16] yields no evidence that the test statistics are significant, indicating that no misspecification is present.

5. Concluding remarks

In this paper, we examine the empirical relationship between the market stock returns and volatility based on seven Asian stock market indexes. Employing the methodology proposed by French et al. (1987), we find that four out of the seven Asian stock markets have a significant relationship between stock returns and unexpected volatility. In general, unexpected volatility has a more significant effect on stock returns than does the expected component.

Further analyzing the relationship between stock returns and time-varying volatility by using a TAR-GARCH(1,1)-in-mean model indicates that the GARCH parameters are highly significant in the daily return series for all of the Asian stock markets studied. However, the size and the significance level of the GARCH effect become smaller in the weekly-return series. With few exceptions, the evidence shows very little GARCH effect on monthly data. An important finding from our study is that the hypothesis of no asymmetric effect is strongly rejected at a high level of significance. Since the sum of estimated coefficients in the variance equation is close to unity, volatility evolution appears to display a persistent fashion. The evidence shows that the asymmetric effect disappears if low frequency data are used.

Notes

1. Bollerslev et al. (1992) provide an excellent review of the various applications of GARCH modeling in finance. The GARCH models have been used to model the daily stock index by French et al. (1987), Akgiray (1989), Connolly (1989), and Ballie and DeGennaro (1990), among others.
2. Studies by Bekaert and Harvey (1997), De Santis and Imrohoroglu (1997), and Kawakatsu and Morey (1999) examine the effects of financial liberalization on stock returns of emerging markets. Chiang (1998) finds some supportive evidence in Asian countries with respect to the relation between stock returns and conditional volatility.
3. The choice of starting period is based on the justification that Asian stock markets became more popular and the issue of globalization became more significant following the stock market crash in October 1987.
4. The study of Indonesian stock market is omitted since these data were not available until September 28, 1990.
5. The formula for the Ljung-Box statistic is $Q(k) = T(T+2)\sum_{j=1}^{k} \rho_j^2/(T-j)$, where ρ_j is the jth lag autocorrelation, k is the number of autocorrelations, and T is the sample size. The null hypothesis is $H_0 : \rho_j = 0$. Rejection of the null hypothesis indicates the presence of serial correlation.
6. Because of the absence of reliable risk-free interest rates for most countries in the Asian area, we use market return instead of excess returns.
7. Econometricians usually use daily data to estimate monthly variance (French et al., 1987; Chou, 1988; Poon and Taylor, 1992; Geyer, 1994). However, in practice, a specific time horizon must be specified n order to generate the variance. The weakness of the specification in equation (3) is in the assumption that the monthly variances are independently generated within a particular month. We are indebted to Ray Chou for making this observation.
8. By using non-overlapping samples of returns, we can obtain a more precise estimate of the volatility for any month by using only returns within that month.
9. Ideally, we should have used out-of-sample data to formulate expectations. French et al. (1987) report that one-step-ahead predictions are similar to those from in-the-sample predictions.
10. Before using the ARIMA model to obtain the predicted volatility, we need to know whether or not the series $\ln(\sigma_{it})$ is stationary. One way to do that is to conduct unit root tests. This can be done by using the Augmented Dickey Fuller (ADF) test developed by Dickey and Fuller (1979). The evidence, which will be provided upon request, indicates that the null hypothesis of having a unit root is rejected, suggesting the confirmation of stationarity.
11. Engle and Ng (1993) find that this model performs better than other asymmetric models in Monte Carlo experiments.
12. Previous empirical studies have shown that a GARCH(1,1) model provides a reasonable fit for stock return data (Akgiray, 1989; Baillie and DeGennaro, 1990; Schwert and Seguin, 1990). To take care of possible asymmetric effect, the TAR-GARCH(1,1) model is used.

13. Again, the choice of using stock returns as the dependent variable is dictated by the lack of reliable interest rates for the Asian stock markets in this study. Some authors also employ market returns in their estimation of the GARCH-M model (Chou, 1988; Baillie and DeGennaro, 1990; Kim and Kon, 1994; Choudhry, 1996).
14. The autoregressive component is used to account for the autocorrelation potentially induced by non-synchronous trading. This problem could be more severe in some Asian stock markets due to a low level of liquidity. The orders of j in the return equation for stock market i are based on the statistical significance evident in Tables 1, 2 and 3.
15. Since the null hypothesis is rejected in several cases, a longer lag specification in the mean equation may be needed.
16. Three tests are designed to examine whether it is possible to use some variables observed in the past to predict the squared standardized residual, $z_t^2 = \varepsilon_t^2/h_t$. Define I_{t-1} as an indicator variable that takes on the value of one when the previous shock in equation (6) is negative and zero otherwise. In the sign-bias test, z_t^2 is regressed on a constant and I_{t-1}. In the negative size-bias test, z_t^2 is regressed on a constant and $I_{t-1}\varepsilon_{t-1}$. In the positive size-bias test, z_t^2 is regressed on a constant and $(1 - I_{t-1})\varepsilon_{t-1}$.

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