Dynamic Linkages among Financial Markets in the Greater China Region: A Multivariate Asymmetric Approach

Kin-Yip Ho¹ and Zhaoyong Zhang²

¹*School of Finance, Actuarial Studies and Applied Statistics, College of Business and Economics, The Australian National University, Canberra and* ²*School of Accounting, Finance and Economics, Edith Cowan University, Perth*

1. INTRODUCTION

THE dynamics of the interrelationships among the financial markets in the Greater China area including Mainland China, Taiwan and Hong Kong is a noteworthy issue of economic research. This is not only because the financial markets in this region have grown rapidly over the past decade but also because of the arguably asymmetric nature of the integration of the Mainland Chinese economy with the rest of the world. Specifically, even though Mainland China has achieved a substantial degree of real economic integration with many advanced countries, she still retains tight controls over her financial markets. Since its establishment in the early 1990s, the Mainland Chinese stock market has expanded rapidly in terms of capitalisation, turnover and the new listings. Even though the stock markets in the Greater China region have developed independently and with different institutional features, cross-market linkages can be observed in terms of the increasing number of Mainland companies listed in the Stock Exchange of Hong Kong and closer economic

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ties in the Greater China region. According to Russell Investment Group, the combined market capitalisation of companies that trade on stock exchanges within Greater China has surpassed the market capitalisation of companies traded on Japanese exchanges in 2007.¹ Some recent studies indicate that there are significant interdependencies among the three markets (Johansson and Ljungwall, 2009).

It is believed that common factors that affect all economies drive financial integration, while the emerging markets are more likely to be influenced by local events (Harvey, 1995). Recently, there have been a number of studies that assess the financial market integration by employing different generalised autoregressive conditional heteroscedasticity (GARCH) models with time-varying conditional correlations (see, for instance, Kim et al., 2005; Hyde et al., 2007; Tai, 2007; Chambet and Gibson, 2008; Kitamura, 2010; Chen et al., 2011). Based on the multivariate volatility framework involving covariances, Tai (2007) finds that all the six Asian markets, India, Korea, Malaysia, Taiwan, Thailand and the Philippines, have become integrated after opening up their markets to foreign investors. Chambet and Gibson (2008) estimate the level of financial integration using a multivariate GARCH model that incorporates time-varying correlations and find that the level of integration of some emerging markets is not only time-varying but also not very high. Hyde et al. (2007) suggest that there is increasing global market integration between the EU and US stock markets with rising conditional correlations in a dynamic correlations GARCH model.

Despite the growing importance of the Greater China stock markets and their dynamic interactions, there have been only a few studies on this issue with mixed results. Groenewold et al. (2004) investigate the interrelationships between prices on the Mainland Chinese share market and those in the neighbouring markets of Hong Kong and Taiwan and find a strong contemporaneous relationship between the two Mainland markets but that the Mainland markets are relatively isolated from the other two markets considered. Cheng and Glascock (2005) examine the linkages among the three Greater China stock markets and two developed markets, Japan and the United States, and find that the three Greater China markets are not cointegrated with either the United States or Japan and the US market has larger influence on the Greater China markets than the Japanese market. Yu et al. (2010) assess the financial market integration in Asia's equity markets by analysing the dynamic correlations in a multivariate volatility framework and conclude that there is rising integration in the Asian equity markets owing to the findings of higher correlations between these equity markets. Chen et al. (2011) employ a multivariate volatil-

¹ According to Russell Investment Group, the combined total for Greater China in 2007 equalled \$5.6 trillion, while the number for Japan sat just below \$5 trillion, and the gap continues to widen.

ity model (MV-GARCH) to quantify the market integration dynamics in Mainland China and find that post-deregulation, the segments appear to be significantly cointegrated between the Chinese A- and B-share markets and the Hong Kong share markets. However, most of these studies have not analysed the volatility dynamics of the Greater China stock markets in a multivariate framework. To the best of our knowledge, there are no studies that have incorporated the significant stylised features pertaining to stock market return volatility into their analyses, even though some papers have examined the time-varying nature of the volatility of the Chinese stock markets (see Tsui and Yu, 1999 and Yeh and Lee, 2000). There is hardly any extensive discussion of the presence of volatility persistence in all the stock markets. This would create potential model misspecification and may generate biased results.

This study proposes a unified approach to the modelling of volatility dynamics of the Greater China area stock markets by adopting a multivariate framework that simultaneously incorporates asymmetries, persistence and dynamic, time-varying correlations. In particular, we adopt two different classes of the generalised autoregressive conditional heteroscedasticity (GARCH) models that nest many popular versions of the GARCH model, to assess the dynamic linkages among the stock markets in the Greater China region and to examine asymmetric volatility and long-memory persistence of shocks in these markets. Strong volatility persistence can have implications for hedging. Our framework ensures the positive-definiteness of the conditional variance–covariance matrix once parameter estimates are obtained. Unlike the bivariate autoregressive conditional heteroscedasticity (ARCH) model of Engle et al. (1984) and the vech representation of Bollerslev et al. (1988), we do not require excessive restrictions on the parameters to guarantee the positive-definiteness of the variance–covariance matrix. Moreover, our multivariate approach is more parsimonious compared with the Baba–Engle–Kraft–Kroner model of Engle and Kroner (1995) and the factor model of Diebold and Nerlove (1989). Parsimony helps to ensure the tractability of estimating the parameters, especially when many data sets are involved. Also, our approach is more efficient than Engle's (2002) dynamic conditional correlation approach, as the parameters for the volatility and correlation equations are concurrently estimated in one step. We believe that it is important to use the multivariate framework to examine the volatility dynamics of the Greater China stock markets, in spite of the potential computational complexities involved. This is partly because many asset returns are subject to similar information or events and their volatilities may be correlated conditional on the given information set. The multivariate framework incorporating the possible asymmetric volatility effects will contribute to our better understanding of the interdependence and integration among the stock markets in the Greater China region. Furthermore, measuring and forecasting financial market volatility is paramount to asset and derivative pricing, asset

allocation, and risk management. Understanding how volatility evolves over time in Greater China's stock markets is particularly important for the development of robust derivative markets in this region.

The rest of this paper is organised as follows. Section 2 outlines the econometric methodology employed in this study. Section 3 then provides brief background information of the stock markets, discusses the data sets employed in this paper and analyses the estimation results. Section 4 concludes with some remarks on the implications of our findings.

2. ECONOMETRIC METHODOLOGY

In this section, we first briefly describe the basic features of the multivariate GARCH(1,1) model with time-varying (dynamic) conditional correlations and then extend the model to incorporate the features of asymmetric volatility and long-memory persistence.

Let $y_t = (y_{1t}, y_{2t}, y_{3t}, \dots, y_{kt})'$ be the k -variate vector of variables with time-varying variance-covariance matrix $\mathbf{H}_t$, and let $\mu_{it}(\xi_i)$ be the arbitrary conditional mean functions that depend on ξ_i , a column vector of parameters, for $i = 1, 2, \dots, k$. A typical k -variate GARCH(1,1) model can be specified as follows:

$$y_{it} = \mu_{it}(\xi_i) + \varepsilon_{it}, \quad i = 1, 2, \dots, k, \quad (1)$$

where $(\varepsilon_{1t}, \varepsilon_{2t}, \varepsilon_{3t}, \dots, \varepsilon_{kt})' | \Phi_{t-1} \sim (0, \mathbf{H}_t)$. Φ_t is the σ -algebra generated by all the available information up to time t . The random disturbance terms ε_{it} and the conditional variance equations h_{iit} are modelled as follows:

$$\varepsilon_{it} = \sqrt{h_{iit}} e_{it}, \quad \text{where } e_{it} \sim N(0, 1), \quad (2)$$

$$h_{iit} = \eta_i + \alpha_i e_{it}^2 + \beta_i h_{iit-1}, \quad i = 1, \dots, k, \quad (3)$$

where (3) is the popular Bollerslev's (1986) GARCH(1,1) model.

Denoting the ij th element ($i, j = 1, 2, \dots, k$) in $\mathbf{H}_t$ by h_{ijt} , the conditional correlation coefficients are given by $\rho_{ijt} = h_{ijt} / \sqrt{h_{iit} h_{jjt}}$. Tse and Tsui (2002) assume that the time-varying conditional correlation matrix $\Gamma_t = \{\rho_{ijt}\}$ is generated by the following recursion

$$\Gamma_t = (1 - \pi_1 - \pi_2)\Gamma + \pi_1 \Gamma_{t-1} + \pi_2 \Psi_{t-1}, \quad (4)$$

where $\Gamma = \{\rho_{ij}\}$ is a time-invariant ($k \times k$) positive-definite correlation matrix, π_1 and π_2 are assumed to be non-negative and sum up to less than 1 and Ψ_t is

a function of the standardised residuals e_{it} . Thus, Γ_t is a weighted average of Γ , Γ_{t-1} and Ψ_{t-1} .

Assuming conditional normality of the variables, the log-likelihood function of the model can be specified as

$$l_t(\theta) = -\frac{1}{2} \log |\mathbf{H}_t| - \frac{1}{2} (\varepsilon_{1t}, \varepsilon_{2t}, \varepsilon_{3t}, \dots, \varepsilon_{kt}) \mathbf{H}_t^{-1} (\varepsilon_{1t}, \varepsilon_{2t}, \varepsilon_{3t}, \dots, \varepsilon_{kt})', \quad (5)$$

where ε_{it} are the random disturbance terms obtained from equation (1) and $\mathbf{H}_t$ is the conditional variance–covariance matrix.

Equations (1–5) summarise the gist of the varying correlations GARCH (VC-GARCH) model of Tse and Tsui (2002). As noted by Tse and Tsui (2002), Bollerslev's (1990) constant-correlations GARCH (CC-GARCH) model is nested within the VC-GARCH model under the restrictions $\pi_1 = \pi_2 = 0$. Thus, the likelihood ratio test can be readily applied to compare the performance of these two models.

To incorporate the feature of asymmetric volatility in the VC-GARCH model, we choose the following two well-established structures, namely the quadratic GARCH(1,1) (QGARCH(1,1)) model proposed by Sentana (1995), which is closely associated with Engle's (1990) asymmetric GARCH (1,1) (AGARCH(1,1)) model, and the asymmetric power ARCH(1,1) (APARCH(1,1)) model of Ding et al. (1993). The QGARCH(1,1) model is specified as follows:

$$h_t = \eta - \gamma \varepsilon_{t-1} + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1}, \quad (6)$$

where γ is the asymmetric coefficient. When $\gamma = 0$, equation (6) becomes the GARCH(1,1) model. The asymmetric power ARCH(1,1) model can be specified as follows:

$$h_t^{\delta/2} = \eta + \alpha (|\varepsilon_{t-1}| - \gamma \varepsilon_{t-1})^\delta + \beta h_{t-1}^{\delta/2}, \quad (7)$$

where γ is the asymmetric coefficient.

To model the long-memory dynamics in volatility, we derive the fractionally integrated asymmetric GARCH (FIAGARCH) model by using the procedure of generalising the conditional variance equations (Baillie et al., 1996). The FIAGARCH(1,d,1) model can be expressed as

$$h_t = \frac{\eta^*}{1 - \beta} + \lambda(L) (\varepsilon_t - \gamma^*)^2, \quad (8)$$

where $\lambda(L) = \sum_{a=1}^{\infty} \lambda_a L^a = 1 - (1 - \beta L)^{-1} (1 - \phi L)(1 - L)^d$. The fractionally integrated asymmetric power ARCH (FIAPARCH) model can also be obtained by using a similar procedure. In particular, the FIAPARCH(1,d,1) model is specified as

$$h_t^{\delta/2} = \frac{\eta}{1-\beta} + \lambda(L)(|\varepsilon_t| - \gamma\varepsilon_t)^\delta. \quad (9)$$

Similar to the FIAGARCH(1,d,1) model, the FIAPARCH(1,d,1) model allows past shocks to have asymmetric effects on the conditional volatility. When γ is greater than 0, negative shocks give rise to higher volatility than positive ones.

The parameters of the different multivariate fractionally integrated GARCH-type models can be estimated using Bollerslev and Wooldridge's (1992) quasi-maximum likelihood estimation approach. To facilitate convergence in the estimation, we have to make appropriate assumptions for the start-up conditions, including the computation of $\lambda(L)$, the number of lags and the initial values. In particular, to compute the response coefficients, $\lambda(L) = \sum_{a=1}^{\infty} \lambda_a L^a = 1 - (1 - \beta L)^{-1}(1 - \phi L)(1 - L)^d$, we adopt the following infinite recursions given in Bollerslev and Mikkelsen (1996):

$$\begin{aligned} \lambda_1 &= \phi - \beta + d, \\ \lambda_b &= \beta\lambda_{b-1} + [(b-1-d)/b - \phi]\zeta_{b-1}, \quad b = 2, \dots, \infty, \end{aligned} \quad (10)$$

where $\zeta_b = \zeta_{b-1}(b-1-d)/b$, with $\zeta_1 = d$. It can be observed from (10) that because b goes to infinity, an appropriate finite truncation is required during estimation. In our calibration, we use 1,000 and 2,000 lags, respectively, and find that the parameter estimates obtained by truncating at 1,000 lags are reasonably close to those based on 2,000 lags. To save computational time, we truncate $\lambda(L)$ after 1,000 lags. As regards the choice of initial values for the estimation procedure, we have experimented with several different values and the results obtained are fairly consistent.

3. EMPIRICAL ANALYSIS

a. Data Description

The following data sets are used to examine the volatility dynamics of the Greater China markets: the Shanghai Composite Index (SHSCOMP), the Shenzhen Composite Index (SHZCOMP), the Taiwan Weighted Index (TAIWGHT), the Hang Seng Index (HNGKNGI), the Shanghai A-share and B-share Indices (SHSASHR, SHSBSHR) and the Shenzhen A-share and B-share Indices (SHZASHR, SHZBSHR). All four markets commenced trading on different dates: the oldest market is the Hong Kong Stock Exchange Ltd, which was formed in 1947, whereas the youngest market is the Shenzhen market, which started on 3 April 1991. The Shanghai market started trading slightly earlier than Shenzhen market on 19 December 1990. During the period from 19 December 1990 to 20 May 1992, the government imposed a daily price limit on the Shanghai market,

which restricted changes to the share price within a 5 per cent band. This limit was finally lifted on 21 May 1992. As such, our analysis of the Greater China stock markets will begin from 22 May 1992. Specifically, for the SHSCOMP, SHZCOMP, TAIWGHT and HNGKNGI Indices, the data sets comprise 3,636 daily price observations spanning from 22 May 1992 to 28 April 2006. As for the A-share and B-share indices, instead of 22 May 1992, the start date of our analysis is 5 October 1992, because this is the very first day of availability for the Shenzhen A-share and B-share indices. All data sets are obtained from DataStream International.

Table 1 displays the key descriptive statistics of the daily returns of the data sets used in this paper.² The daily returns are computed on a continuously compounding basis by taking the difference of the logarithms of the daily stock market price indices. As shown in Table 1, excess kurtosis is noted for all markets, and the Shanghai Composite Index has the highest kurtosis coefficient. Also, as measured by the standard deviation of the data sets, the Shanghai and the Shenzhen Composite Indices are relatively more volatile. This observation is apparently consistent with papers that highlight the fact that emerging stock markets are generally more volatile than their developed counterparts (see Aggarwal et al., 1999; Gao, 2002 and Bekaert and Harvey, 2007). The McLeod-Li, ARCH LM and QARCH LM tests suggest that conditional heteroscedasticity may be present in all the data series. This finding is further corroborated by the BDS test. Under the null hypothesis of independence, the BDS test statistic has an asymptotic standard normal distribution.

b. Empirical Results

We estimate respectively three different combinations of the stock markets in the Greater China region, with the first group including HKNGI, TWGHI, CHSCOMP and CHZCOMP, the second group consisting of HKNGI, TWGHI, CHSASHR and CHZASHR and the third group including HKNGI, TWGHI, CHSBSHR and CHZBSHR. Because of the space limitation and also the similarity of the results, we report in Table 2 the estimation results of the VC-GARCH, VC-QGARCH and VC-APARCH for the first group and the estimation results of FIAGARCH and FIAPARCH in Table 3 only. The results for the rest are available upon request from the authors.

² The results for SHSASHR, SHSBSHR, SHZASHR and SHZBSHR are not reported but available upon request. It is interesting to note that there is a significant disparity in the kurtosis coefficients between the A-share and B-share markets. For instance, the kurtosis coefficient of the Shanghai A-share market is 27.6047, whereas that of the B-share market is only 8.3140. In addition, the standard deviation figures suggest that the A-share markets are more volatile than their B-share counterparts, but as we will demonstrate later on, this finding is more apparent than real, because there are periods in which the B-share markets exhibit greater fluctuations.

TABLE 1
Summary Statistics of Stock Index Returns (22 May 1992–28 April 2006)

<i>Variable</i>	<i>CHSCOMP</i>	<i>CHZCOMP</i>	<i>HNGKNGI</i>	<i>TAIWGHT</i>
Mean	0.0000	0.0001	0.0003	0.0001
Median	0.0000	0.0000	0.0000	0.0000
Maximum	0.2886	0.2722	0.1725	0.0852
Minimum	-0.1791	-0.1888	-0.1473	-0.0994
Std. Dev.	0.0244	0.0222	0.0162	0.0158
Skewness	1.5013	0.8738	0.0327	-0.0391
Kurtosis	24.3797	20.2359	13.2061	5.7497
Observations	3,636	3,636	3,636	3,636
Ljung–Box Q statistic				
5 Lags	27.0119	26.7411	31.6219	20.6267
10 Lags	51.2207	41.8347	39.0681	32.8729
McLeod–Li test				
5 Lags	701.2005	351.2478	961.3332	193.0676
10 Lags	864.0146	401.5340	1033.7274	327.3346
ARCH LM Test				
5 Lags	451.5436	248.3246	563.4687	134.0914
10 Lags	475.7342	254.5937	577.6507	192.3085
QARCH LM Test				
1 Lag	83.0659	38.9457	509.7766	52.2148
4 Lags	510.7748	380.5109	953.4219	218.7134
BDS test				
$e = 1, l = 3$	24.8321	26.1436	10.1311	6.4830
$e = 1, l = 4$	28.5918	30.8695	11.8978	8.7147
$e = 1, l = 5$	31.5809	35.1277	13.5199	10.1641
$e = 1.5, l = 3$	24.6742	23.1696	12.4218	7.6961
$e = 1.5, l = 4$	27.2365	26.0835	14.2512	9.9417
$e = 1.5, l = 5$	28.5700	28.3620	15.8442	11.5868
Runs test				
R_1	-2.2050	-4.3528	-1.9287	-1.6067
R_2	-11.4874	-12.9865	-3.5001	-0.7172
R_3	-14.9279	-14.5654	-4.5451	-2.8163

Notes:

(i) CHSCOMP = Shanghai Composite Index, CHZCOMP = Shenzhen Composite Index, HNGKNGI = Hong Kong Hang Seng Index, TAIWGHT = Taiwan Stock Exchange Weighted Index.

(ii) QARCH LM test statistic is attributable to Sentana (1995), and it is distributed as chi-squared with $q(q + 3)/2$ degrees of freedom, where q is the number of lags.

(iii) For the BDS test, l represents the correlation dimension, whereas e represents the distance between pairs of consecutive observations, measured as a multiple of the standard deviation of the series. Under the null hypothesis of independence, the test statistic is asymptotically distributed as standard normal.

(iv) For the runs test, R_i for $i = 1, 2$ and 3 denote the runs tests of the series R_t , IRI_t and R_{12} respectively. Under the null hypothesis that successive observations in the series are independent, the test statistic is asymptotically standard normal.

(i) Volatility Asymmetries

As it can be seen from Tables 2 and 3, there is significant evidence that corroborates the existence of asymmetries in the volatility of the Taiwan and Hong Kong stock markets. Both markets exhibit the leverage effect, whereby

TABLE 2
Estimation Results of Group 1 Stock Indices (22 May 1992–28 April 2006)

Variable	η	β	α	γ	δ	μ_0	μ_1	Γ	π_1	π_2	LL (VC)	Corr (CC)	LL (CC)
Panel A: VC-GARCH													
TAIWGHT	0.0817 (0.0271)	0.9048 (0.0181)	0.0679 (0.0121)	–	–	0.0451 (0.0285)	0.0289 (0.0171)	$\rho_{TH} = 0.3701$ (0.0640)	0.9661 (0.0057)	0.0242 (0.0036)	–9958.9682	$\rho_{TH} = 0.2414$ (0.0183)	–11107.55048
HNGKNGI	0.0322 (0.0113)	0.9163 (0.0126)	0.0751 (0.0119)	–	–	0.0575 (0.0235)	0.0397 (0.0179)	$\rho_{TS} = 0.0633$ (0.0519)				$\rho_{TS} = 0.0262$ (0.0171)	
								$\rho_{TZ} = 0.0675$ (0.0526)				$\rho_{TZ} = 0.0273$ (0.0179)	
CHSCOMP	0.0178 (0.0102)	0.9390 (0.0134)	0.0671 (0.0144)	–	–	–0.0287 (0.0379)	0.0211 (0.0155)	$\rho_{HS} = 0.0182$ (0.0260)				$\rho_{HS} = 0.0431$ (0.0169)	
CHZCOMP	0.0183 (0.0115)	0.9389 (0.0149)	0.0667 (0.0155)	–	–	–0.0458 (0.0404)	0.0259 (0.0154)	$\rho_{HZ} = 0.0310$ (0.0263)				$\rho_{HZ} = 0.0543$ (0.0169)	
								$\rho_{SZ} = 0.9947$ (0.0050)				$\rho_{SZ} = 0.8647$ (0.0125)	
Panel B: VC-QGARCH													
TAIWGHT	0.1429 (0.0500)	0.8709 (0.0292)	0.0796 (0.0144)	0.1015 (0.0328)	–	0.0003 (0.0008)	0.0333 (0.0177)	$\rho_{TH} = 0.3665$ (0.0651)	0.9661 (0.0059)	0.0245 (0.0037)	–9893.65	$\rho_{TH} = 0.2385$ (0.0179)	–11047.32616
HNGKNGI	0.0490 (0.0151)	0.9087 (0.0130)	0.0753 (0.0108)	0.0629 (0.0216)	–	0.0201 (0.0234)	0.0486 (0.0183)	$\rho_{TS} = 0.0530$ (0.0740)				$\rho_{TS} = 0.0226$ (0.0165)	
								$\rho_{TZ} = 0.0553$ (0.0750)				$\rho_{TZ} = 0.0263$ (0.0174)	
CHSCOMP	0.0213 (0.0109)	0.9390 (0.0131)	0.0659 (0.0137)	0.0319 (0.0145)	–	–0.0613 (0.0641)	0.0190 (0.0202)	$\rho_{HS} = 0.0109$ (0.0443)				$\rho_{HS} = 0.0395$ (0.0193)	
								$\rho_{HZ} = 0.0205$ (0.0454)				$\rho_{HZ} = 0.0511$ (0.0192)	
								$\rho_{SZ} = 0.9953$ (0.0051)				$\rho_{SZ} = 0.8628$ (0.0127)	

TABLE 2 *Continued*

<i>Variable</i>	η	β	α	γ	δ	μ_0	μ_1	Γ	π_1	π_2	<i>LL (VC)</i>	<i>Corr (CC)</i>	<i>LL (CC)</i>
CHZCOMP	0.0223 (0.0120)	0.9387 (0.0139)	0.0660 (0.0142)	0.0353 (0.0147)	–	–0.0798 (0.0638)	0.0235 (0.0191)						
Panel C: VC-APARCH													
TAIWGHT	0.1031 (0.0353)	0.8866 (0.0240)	0.0747 (0.0147)	0.2614 (0.0659)	1.8911 (0.3014)	0.0004 (0.0009)	0.0361 (0.0180)	$\rho_{TH} = 0.3716$ (0.0652)	0.9669 (0.0058)	0.0240 (0.0037)	–9863.3766	$\rho_{TH} = 0.2386$ (0.0179)	–10935.42112
HNGKNGI	0.0328 (0.0102)	0.9220 (0.0105)	0.0743 (0.0101)	0.3219 (0.0720)	1.4397 (0.1712)	0.0122 (0.0285)	0.0499 (0.0180)	$\rho_{TS} = 0.0538$ (0.0562)				$\rho_{TS} = 0.0253$ (0.0176)	
								$\rho_{TZ} = 0.0556$ (0.0571)				$\rho_{TZ} = 0.0267$ (0.0178)	
CHSCOMP	0.0149 (0.0078)	0.9430 (0.0110)	0.0720 (0.0130)	0.1545 (0.0522)	1.5711 (0.1530)	–0.0830 (0.0595)	0.0198 (0.0181)	$\rho_{HS} = 0.0045$ (0.0280)				$\rho_{HS} = 0.0386$ (0.0177)	
CHZCOMP	0.0154 (0.0089)	0.9414 (0.0122)	0.0723 (0.0146)	0.1541 (0.0500)	1.6379 (0.1700)	–0.1015 (0.0589)	0.0252 (0.0178)	$\rho_{HZ} = 0.0140$ (0.0297)				$\rho_{HZ} = 0.0511$ (0.0177)	
								$\rho_{SZ} = 0.9949$ (0.0053)				$\rho_{SZ} = 0.8769$ (0.0105)	

Notes:

(i) All standard errors (in parenthesis) are the heteroscedastic-consistent Bollerslev–Wooldridge standard errors computed based on the quasi-maximum likelihood estimation technique.

(ii) Log-likelihood value (VC) and log-likelihood value (CC) refer to the likelihood values obtained from the VC-GARCH(1,1) and CC-GARCH(1,1) models, respectively.

(iii) Correlations (CC) refer to the conditional correlation coefficient obtained from the constant-correlation models.

TABLE 3
Estimation Results of Group 1 Stock Indices (22 May 1992–28 April 2006)

Variable	η	ϕ	γ	δ	β	d	μ_0	μ_1	Γ	π_1	π_2	Corr (CC)
Panel A: VC-FIAGARCH												
TAIWGHT	-0.2218 (0.1850)	-0.0911 (0.0902)	0.8300 (0.1338)	-	0.1053 (0.1085)	0.2874 (0.0370)	0.0114 (0.0192)	0.0328 (0.0173)	$\rho_{TH} = 0.4029$ (0.0675)	0.9695 (0.0047)	0.0232 (0.0032)	$\rho_{TH} = 0.2368$ (0.0182)
HNGKNGI	-0.0500 (0.1103)	0.1380 (0.1690)	0.5623 (0.1619)	-	0.3671 (0.2105)	0.3222 (0.0609)	0.0277 (0.0240)	0.0505 (0.0182)	$\rho_{TS} = 0.0765$ (0.0661)			$\rho_{TS} = 0.0186$ (0.0185)
									$\rho_{TZ} = 0.0699$ (0.0660)			$\rho_{TZ} = 0.0219$ (0.0193)
CHSCOMP	0.1316 (0.0621)	0.1569 (0.0965)	0.2334 (0.1067)	-	0.3652 (0.0939)	0.3516 (0.0433)	-0.0700 (0.0620)	0.0306 (0.0185)	$\rho_{HS} = 0.0375$ (0.0617)			$\rho_{HS} = 0.0416$ (0.0167)
CHZCOMP	0.0937 (0.0642)	0.1420 (0.0979)	0.3071 (0.0956)	-	0.3679 (0.0962)	0.3650 (0.0384)	-0.0870 (0.0610)	0.0363 (0.0186)	$\rho_{HZ} = 0.0430$ (0.0587)			$\rho_{HZ} = 0.0514$ (0.0165)
									$\rho_{SZ} = 0.9847$ (0.0063)			$\rho_{SZ} = 0.8214$ (0.0109)
Panel B: VC-FIAPARCH												
TAIWGHT	0.3912 (0.1307)	-0.0905 (0.1039)	0.2828 (0.0693)	1.8214 (0.2183)	0.1367 (0.1286)	0.2787 (0.0450)	0.0095 (0.0236)	0.0367 (0.0179)	$\rho_{TH} = 0.4017$ (0.0693)	0.9685 (0.0053)	0.0241 (0.0035)	$\rho_{TH} = 0.2354$ (0.0182)
HNGKNGI	0.1532 (0.0818)	0.1915 (0.1528)	0.3355 (0.0936)	1.7817 (0.1634)	0.4391 (0.2365)	0.3200 (0.0914)	0.0209 (0.0243)	0.0522 (0.0178)	$\rho_{TS} = 0.0780$ (0.0711)			$\rho_{TS} = 0.0194$ (0.0153)
									$\rho_{TZ} = 0.0691$ (0.0702)			$\rho_{TZ} = 0.0227$ (0.0161)
CHSCOMP	0.1565 (0.0703)	0.1521 (0.0954)	0.1079 (0.0477)	1.9811 (0.1734)	0.3736 (0.0921)	0.3731 (0.0440)	-0.0742 (0.0600)	0.0326 (0.0209)	$\rho_{HS} = 0.0288$ (0.0825)			$\rho_{HS} = 0.0429$ (0.0168)
CHZCOMP	0.1329 (0.0818)	0.1236 (0.1001)	0.1309 (0.0442)	1.9967 (0.1857)	0.3640 (0.0984)	0.3916 (0.0396)	-0.0914 (0.0591)	0.0386 (0.0209)	$\rho_{HZ} = 0.0323$ (0.0788)			$\rho_{HZ} = 0.0520$ (0.0168)
									$\rho_{SZ} = 0.9845$ (0.0068)			$\rho_{SZ} = 0.8335$ (0.0132)

Note:

(i) Corr(CC) are the coefficients of the constant conditional correlation model. The Bollerslev-Wooldridge (1992) standard errors are reported in parentheses.

negative shocks have a greater impact on future volatility levels than positive shocks of the same magnitude. Apparently, this finding is robust to changes in model specification and time periods. Our findings for the Taiwan Weighted Index are consistent with the study of Hsin et al. (2003), who observe asymmetric effects in volatility for most of their sample firms.

The results for the Mainland Chinese markets are a little mixed. The return volatility of the Shenzhen Composite Index displays significant leverage effect for the VC-QGARCH, VC-APARCH, VC-FIAPARCH and VC-FIAPARCH models, which is reasonably consistent across different time periods. A similar pattern is found for the Shanghai Composite Index although most of the estimated values of γ are significant at the 10 per cent level. It is interesting to note that the return volatility of the A-share markets exhibit some evidence of significant asymmetries, but not in the B-share markets.³ This difference between the A- and B-share markets could be attributed to the differences in the informational environments of both markets. In contrast, given that the B-shares are denominated in US or Hong Kong dollars and sold mainly to foreign investors, their registration requires financial statements to be prepared based on International Accounting Standards. The information environment for type B-shares includes disclosure of financial statements in the documentation of the initial public offering. In addition, the investment funds that own B-shares represent sophisticated foreign investors who monitor the issuing firms' activities and decisions. These shares were relatively insulated from trade manipulation by insiders or state officials (Abdel-Khalik et al., 1999). Thus, the informational environment of firms issuing B-shares is relatively formalised, and the investors in B-share markets have better access to higher-quality news. Diversity of predictions may therefore be smaller compared with the A-share markets, and this in turn explains the lack of asymmetry in the B-share markets.

(ii) Persistence

We now turn to the issue of volatility persistence. As shown in Tables 2 and 3, the sum of the GARCH parameters ($\alpha + \beta$) for all the stock markets is very close to unity, which apparently indicates the presence of strong persistence in volatility (see Bollerslev and Engle, 1993 and Baillie et al., 1996). This finding provides some motivation for us to model the long-range dependence using the approach of fractional integration. In particular, we measure the persistence of volatility

³ A comprehensive in-depth explanation of the volatility asymmetry of the Greater China stock markets is beyond the scope of this study. However, some preliminary conjectures would be that, based on the results obtained from developed stock markets, many existing papers concluded that negative shocks (bad news) engendered higher volatility levels than positive shocks (good news) of the same magnitude, which are likely due to the financial leverage effect (Black, 1976); the volatility feedback effects (French et al., 1987; McQueen and Vorkink, 2004); and the presence of investors with heterogeneous expectations in the stock market (Yamamoto, 2006; Li, 2007).

with the fractional differencing (long memory) parameter d in the VC-FIGARCH, VC-FIAPARCH and VC-FIAGARCH models. Table 4 summarises the estimation results of the fractional differencing parameter. As it can be seen from Table 4, the estimated values of the fractional differencing parameter d for all the markets range from 0.2 to 0.42 and are significantly different from zero and one. This suggests that either the usual GARCH or the integrated GARCH (IGARCH) models are inadequate compared with the fractionally integrated version. The results also indicate that the estimated values of d are very sensitive to the model specifications and can vary significantly for the same stock index, especially in the cases of TAIWGHT and HNGKNGI. For the latter, the value of d seems to be higher with the VC-FIGARCH model than with the VC-FIAPARCH and the

TABLE 4
Fractional Differencing Parameter d

	<i>VC-FIGARCH</i>	<i>VC-FIAGARCH</i>	<i>VC-FIAPARCH</i>
Group 1			
TAIWGHT	0.3415 (0.0545)	0.2874 (0.0370)	0.2787 (0.0450)
HNGKNGI	0.4010 (0.0729)	0.3222 (0.0609)	0.3200 (0.0914)
CHSCOMP	0.3624 (0.0450)	0.3516 (0.0433)	0.3731 (0.0440)
CHZCOMP	0.3844 (0.0423)	0.3650 (0.0384)	0.3916 (0.0396)
Group 2			
TAIWGHT	0.3423 (0.0566)	0.2903 (0.0376)	0.2731 (0.0468)
HNGKNGI	0.4164 (0.0776)	0.3394 (0.0641)	0.3665 (0.1005)
CHSASHR	0.3807 (0.0427)	0.3695 (0.0412)	0.4002 (0.0450)
CHZASHR	0.3899 (0.0414)	0.3698 (0.0377)	0.4057 (0.0414)
Group 3			
TAIWGHT	0.3320 (0.0536)	0.2808 (0.0404)	0.2673 (0.0445)
HNGKNGI	0.4129 (0.0863)	0.3356 (0.0769)	0.3917 (0.1208)
CHSBSHR	0.3581 (0.0627)	0.3576 (0.0720)	0.3950 (0.0609)
CHZBSHR	0.2806 (0.0328)	0.2792 (0.0454)	0.2787 (0.0415)

Notes:

(i) The Bollerslev–Wooldridge (1992) standard errors are given in parentheses. (ii) Group 1: Taiwan Weighted Index (TAIWGHT), Hong Kong Hang Seng Index (HNGKNGI), Shanghai Composite Index (CHSCOMP) and Shenzhen Composite Index (CHZCOMP). Group 2: TAIWGHT, the HNGKNGI, the Shanghai A-Share Index (CHSASHR), and the Shenzhen A-Share Index (CHZASHR). Group 3: TAIWGHT, HNGKNGI, the Shanghai B-Share Index (CHSBSHR) and the Shenzhen B-Share Index (CHZBSHR).

VC-FIAGARCH models. As the latter two models nest the VC-FIARCH model, this may suggest that ignoring the feature of asymmetry could overestimate the degree of long-range persistence in volatility. It is also noted that the estimated values of d obtained from the different Mainland Chinese stock market series are quite similar, and the differences between the A-share and B-share markets are not very substantial.

Judging from the estimated values of the parameter d , there could be a common degree of fractional integration/long memory among some of the markets. For instance, in group 1, the values of d for TAIWGHT are 0.2874 and 0.2787 for the VC-FIAGARCH and VC-FIARCH models, respectively, which are similar to the corresponding ones for HNGKNGI. As for the two Mainland Chinese markets, the estimated values of d are remarkably close, with a value ranging from 0.3516 to 0.3731 for the three models estimations. The possible presence of co-persistence has important implications for asset pricing relationships and making optimal decisions related to portfolio allocation.

The phenomenon of volatility persistence is a complex issue with no easy explanations. The existence of volatility persistence may be explained by the presence of a serially correlated news arrival process (otherwise known as the 'information processing hypothesis') and heterogeneous expectations (Engle et al., 1990; Gaunersdorfer, 2000), the imitative behaviour of investors in the stock market (Yamamoto, 2006), the preferences of risk-averse agents in equilibrium asset pricing models (McQueen and Vorkink, 2004), and the belief systems of traders in a stock market (Brock and Hommes, 1998). For the latter, the authors argue that persistent volatility is caused by traders experimenting with different belief systems based upon past profit experience and their estimates of future profit experience. The agents in the model have adaptive beliefs, which induce them to adapt their trading strategies on a time scale that is slower than the time scale on which the trading process takes place. Volatility persistence enters returns through a slower time scale of changes in beliefs. A combination of these explanations may help us understand the existence of volatility persistence in the Greater China stock markets.

(iii) Time-varying Correlations

Table 5 and Figure 1 present the main findings for the time-invariant component of the correlation matrix, $\Gamma = \{\rho_{ij}\}$. It can be seen from Figure 1 that the estimated values of the pairwise correlation coefficient for any two indices (the time-invariant component of Γ , $\Gamma = \{\rho_{ij}\}$) with different specifications are apparently similar. It is interesting to note that the markets both within and outside Mainland China show a high correlation, but not in between (Table 5). The Shanghai and Shenzhen Composite Indices have the highest correlation coefficient, but not perfectly unity. This is consistent with the observation by Gao (2002) that what is most 'unusual' about China's dual stock exchange

TABLE 5
Conditional Correlation Matrix Γ_t

<i>Model</i>	<i>VC-QGARCH</i>	<i>VC-APARCH</i>	<i>VC-FIAGARCH</i>	<i>VC-FIAPARCH</i>
Group 1				
TAIWGHT-HNGKNGI	0.3665 (0.0651)	0.3716 (0.0652)	0.4029 (0.0675)	0.4017 (0.0693)
TAIWGHT-CHSCOMP	0.0530 (0.0740)	0.0538 (0.0562)	0.0765 (0.0661)	0.0780 (0.0711)
TAIWGHT-CHZCOMP	0.0553 (0.0750)	0.0556 (0.0571)	0.0699 (0.0660)	0.0691 (0.0702)
HNGKNGI-CHSCOMP	0.0109 (0.0443)	0.0045 (0.0280)	0.0375 (0.0617)	0.0288 (0.0825)
HNGKNGI-CHZCOMP	0.0205 (0.0454)	0.0140 (0.0297)	0.0430 (0.0587)	0.0323 (0.0788)
CHSCOMP-CHZCOMP	0.9953 (0.0051)	0.9949 (0.0053)	0.9847 (0.0063)	0.9845 (0.0068)
π_1	0.9661 (0.0059)	0.9669 (0.0058)	0.9695 (0.0047)	0.9685 (0.0053)
π_2	0.0245 (0.0037)	0.0240 (0.0037)	0.0232 (0.0032)	0.0241 (0.0035)
Group 2				
TAIWGHT-HNGKNGI	0.3208 (0.0507)	0.3240 (0.0501)	0.3514 (0.0533)	0.3434 (0.0510)
TAIWGHT-CHSASHR	0.0631 (0.0628)	0.0626 (0.0498)	0.0805 (0.0571)	0.0770 (0.0530)
TAIWGHT-CHZASHR	0.0618 (0.0630)	0.0610 (0.0506)	0.0724 (0.0579)	0.0689 (0.0535)
HNGKNGI-CHSASHR	0.0115 (0.1039)	0.0094 (0.0341)	0.0278 (0.0488)	0.0250 (0.0479)
HNGKNGI-CHZASHR	0.0405 (0.1006)	0.0363 (0.0357)	0.0583 (0.0477)	0.0528 (0.0479)
CHSASHR-CHZASHR	0.9859 (0.0041)	0.9850 (0.0041)	0.9745 (0.0054)	0.9758 (0.0056)
π_1	0.9502 (0.0077)	0.9499 (0.0078)	0.9560 (0.0058)	0.9538 (0.0069)
π_2	0.0330 (0.0043)	0.0330 (0.0043)	0.0313 (0.0038)	0.0323 (0.0039)
Group 3				
TAIWGHT-HNGKNGI	0.3764 (0.0686)	0.3772 (0.0676)	0.3854 (0.0687)	0.3770 (0.0635)
TAIWGHT-CHSBSHR	-0.0075 (0.0735)	-0.0042 (0.0750)	0.0129 (0.3799)	0.0027 (0.0699)
TAIWGHT-CHZBSHR	0.0185 (0.0718)	0.0177 (0.0749)	0.0436 (0.3165)	0.0342 (0.0653)
HNGKNGI-CHSBSHR	0.1350 (0.0687)	0.1241 (0.0679)	0.1483 (0.1264)	0.1355 (0.0654)
HNGKNGI-CHZBSHR	0.1078 (0.0660)	0.1040 (0.0655)	0.1266 (0.1116)	0.1115 (0.0623)
CHSBSHR-CHZBSHR	0.8399 (0.0432)	0.8493 (0.0412)	0.8553 (0.0376)	0.8445 (0.0394)

TABLE 5 *Continued*

<i>Model</i>	<i>VC-QGARCH</i>	<i>VC-APARCH</i>	<i>VC-FIAGARCH</i>	<i>VC-FIAPARCH</i>
π_1	0.9764 (0.0043)	0.9763 (0.0044)	0.9770 (0.0029)	0.9772 (0.0030)
π_2	0.0183 (0.0027)	0.0182 (0.0027)	0.0179 (0.0019)	0.0180 (0.0020)

Notes:
(i) The Bollerslev–Wooldridge (1992) standard errors are given in parentheses. (ii) Group 1: Taiwan Weighted Index (TAIWGHT), Hong Kong Hang Seng Index (HNGKNGI), Shanghai Composite Index (CHSCOMP) and Shenzhen Composite Index (CHZCOMP). Group 2: TAIWGHT, the HNGKNGI, the Shanghai A-Share Index (CHSASHR) and the Shenzhen A-Share Index (CHZASHR). Group 3: TAIWGHT, HNGKNGI, the Shanghai B-Share Index (CHSBSHR) and the Shenzhen B-Share Index (CHZBSHR).

FIGURE 1
Conditional Correlations (VC-FIAPARCH)

system is that the stocks traded on the two exchanges perform quite differently, despite the fact that the two exchanges in China do not have large differences in their sector representation, quotation systems and trading schemes. Xu (2000) also notes that one difference between the two markets is that, while most companies listed on the Shanghai market are large and state-owned, those on the Shenzhen market are small joint ventures and export-oriented. Apart from the dissimilar characteristics of the companies listed in these two markets, the relative size of these two exchanges has undergone major changes. Beginning with a similar size to the Shenzhen exchange at the end of 1992, the market capitalisation of the Shanghai exchange has grown to over 4.5 times as large as that of the Shenzhen exchange at the end of 1994.

Given the increasing importance of trade and business linkages in the Greater China region especially in the recent years (see Zhang et al., 2003), it may be a bit surprising to note that the correlation between the Mainland Chinese markets and the rest of the Greater China region is remarkably weak.⁴ The possible explanations for such lower correlation level include Mainland China's non-convertibility of the RMB, capital controls as well as restriction/regulations on both Shanghai and Shenzhen stock exchanges.⁵ Moreover, as the conditional correlation matrix that we are estimating includes the effects of all the markets, the estimation results of the time-varying coefficients reflect not only the dynamics of the Mainland Chinese markets but also the relationship between Taiwan and Hong Kong markets. Thus, the results are suggesting that at certain points in time, the conditional correlations for these markets may strengthen above the usual weak level, depending on how market dynamics evolve over time. This explanation is apparently consistent with the recent literature on the time-varying nature of the correlations of international stock markets (see, for example, Huyghebaert and Wang, 2010).

There are several observations worth mentioning for the dynamic component of Γ_t . First, the conditional correlation between any two markets is significantly time-varying. As shown in Tables 2 and 3, the parameters π_1 and π_2 are individually significant at the one per cent level, and the constant-correlation models are rejected by the likelihood ratio tests. The graphs also provide some qualitative support for the existence of varying conditional correlations. Second, the time paths of the correlation between the Mainland Chinese markets and the Hong Kong and Taiwan markets do not exhibit any distinctive upward or downward trend. No predictable patterns are discernible from the graphs in Figure 1. Third, there is, however, some qualitative evidence that the correlation between TAIWGHT and HNGKNGI is strengthening over time. In particular, the conditional correlation between the Hong Kong and the Taiwan stock markets seems to increase from 1998 onwards. The reason could be due to increasing financial integration within the Asian region in recent years.⁶ Last,

⁴ Gao (2002) and Groenewold et al. (2004) reported similar findings that, in comparison with other markets, China displays low correlation with the world's major developed markets, in particular, the markets in Europe, the United States and Japan.

⁵ Following the suggestion of an anonymous referee, we have re-run the models using more recent data with different time periods ending, respectively, in December 2007, December 2008, December 2009 and December 2010 to examine the robustness of our estimation results. The results are very similar to what we have reported. The unconditional correlation coefficients remain rather weak (between 0.1 and 0.2) and are usually not very significant. However, the time-varying coefficients are usually statistically significant. This suggests that the varying degrees of connectedness among the Greater China stock markets over time matter in explaining the dynamic integration of these markets.

⁶ Our finding is apparently consistent with research focusing on the financial integration of international equity markets, such as Cheung et al. (2003), Chi et al. (2006), Cowen et al. (2006) and Leong and Felmingham (2003).

as it can be seen from Figure 1, the correlation between the CHSCOMP and the CHZCOMP Indices has been strengthening over time and the conditional correlations between the two markets have undergone dramatic changes at different points in time. Three different periods are distinguishable: the first period occurs in the early 1990s, during which the correlation coefficient fluctuates between 0.4 and 0.6. After mid-1993, the correlation coefficient begins to strengthen and exhibits an upward trend up to 1996. In the third period after 1996, the correlation dips slightly before it rises again gradually and remains at values close to 1.0.

(iv) Volatility Dynamics

Figure 2 displays the return volatility patterns of the A-share and B-share markets in Mainland China. It can be seen from Figure 2 that the volatility of the A-share markets is much higher than that of the B-share markets prior to April 1997. However, the volatility disparity between the two markets is reversed post-1997, namely the B-share market appears to be more volatile than the A-share market. As discussed earlier, the volatility disparity between the A-share and B-share markets may be due to the differences in the information environment, the market-making costs and the recent rapid development of the B-share market. Since 1996, there were several regulatory changes pertaining to

FIGURE 2
Conditional Volatility (A-share, B-share)

the informational environment instituted by the authorities, including the compulsory information disclosure requirements in stock and fund trading in March 1997 and the direct supervision of the A-share market under the Central Security Regulation Council in August 1997. These regulatory measures could have improved the information environment in the A-share market in recent years and thereby reduced market volatility. Then, the differences in the market-making costs between the two markets could also be another possible cause of the volatility disparity. The B-share markets in China are found to contain higher informed trading and other market-making costs than the A-share markets (He et al., 2003). When informed trading and other cost components are accounted for, the volatility disparity between the A- and B-shares decreases. Finally, the recent developments in the B-share markets could also have triggered volatility levels that were higher than those in the A-share markets. This could be induced by major events and news affecting the B-share markets, including the speculation of merger between A- and B-shares and changes in market supervision in the B-share market since 2000.⁷ The results also indicate that volatility can change dramatically over time, implying that conclusion based on unconditional standard deviation of the market returns can be misleading. This finding underscores the importance of analysing conditional instead of unconditional volatility.

To compare the volatility levels of the different pairs of markets in the Great China region, we extract and report the results based on the output from the VC-FIAPARCH model in Figure 3 only, as the graphs based on other models are qualitatively similar. These figures further confirm the findings that the Mainland Chinese markets may appear to be more volatile than Hong Kong and Taiwan markets if measured by using unconditional standard deviation. However, if we consider the conditional volatility levels of the Greater China stock markets, there are significant periods in which the Mainland Chinese markets actually exhibit lower volatility than the markets in Taiwan and Hong Kong. Furthermore, the disparity in volatility level between the Shanghai and Shenzhen markets is not very substantial, especially prior to 2001. The B-share markets, for most of the time, exhibit higher volatility levels than that in Taiwan and Hong Kong.

Finally, we make an assessment of the models used in this study. Table 6 reports the results of the likelihood ratio tests for each model. It is noted that models with varying correlations generally outperform those with constant correlations, based on log-likelihood ratio tests and residual diagnostics. In fact, there are instances in which the estimation of the constant-correlation model failed because of non-convergence. This could also be an indication that the

⁷ In September 2006, the FTSE Xinhua Index report stated that China's B-shares leapt in price during September amid rumours that the government might allow the A-shares and B-shares to merge.

FIGURE 3
Conditional Volatility (VC-FIAPARCH)

restriction of constant correlation is inappropriate. It is also noted that the APARCH class of models yielded more satisfactory results than the AGARCH class, because, in some cases, the estimation of the AGARCH models resulted in negative parameter estimates. These cases can be found in the estimation of VC-FIAGARCH for the TAIWGHT and HNGKNGI Indices. This finding is consistent with some of the existing studies.⁸

4. CONCLUSION

In this study, we have analysed the volatility dynamics of the stock markets of the Greater China region using the daily returns data from 1992 to 2006 and found the existence of volatility persistence and asymmetries. In particular, the results show that only the B-share markets do not exhibit statistically significant asymmetries, and this result is consistent across different model specifications.

⁸ This problem is not new in the literature (see Engle, 1982). We have tried the class of EGARCH models, which admit negative parameter estimates, but there are problems of convergence. A drawback of the EGARCH class, as noted by Pagan (1996), is that the IEGARCH model is not identifiable by the quasi-maximum likelihood; therefore, if d tends to one, the same problem is likely to occur for the FIEGARCH model. Furthermore, unlike the rest of the models in the ARCH family, the volatility level of EGARCH model is based on the standardised innovations rather than the innovations (excess returns) themselves.

TABLE 6
Likelihood Ratio Tests

<i>Model</i>	<i>LL</i>	<i>Model</i>	<i>LL</i>	<i>LR</i>
Group 1				
CC-FIAPARCH	-10902.5363	VC-FIAPARCH	-9733.6106	2337.8514
CC-FIAGARCH	-10930.9398	VC-FIAGARCH	-9747.5383	2366.8029
Group 2				
CC-FIAPARCH	-10340.1670	VC-FIAPARCH	-9289.5970	2101.1402
CC-FIAGARCH	-10363.2517	VC-FIAGARCH	-9298.0113	2130.4808
Group 3				
CC-FIAPARCH	-11328.1771	VC-FIAPARCH	-10899.9539	856.4464
CC-FIAGARCH	-11353.8893	VC-FIAGARCH	-10912.2470	883.2846

Note:

(i) LL, log-likelihood value; LR, likelihood ratio statistic.

Also, conditional correlations among the markets are significantly time-varying. There is some evidence that correlations between some markets are strengthening over time. Judging from the unconditional standard deviation of the returns of the various indices, it appears that the A-share market is more volatile than the B-share market and that the Mainland Chinese markets exhibit greater fluctuations than their counterparts in Hong Kong and Taiwan. However, this claim is misleading when we analyse the conditional volatility of all the markets, because the B-share markets are apparently more volatile than the A-share markets after 1997. Furthermore, there are some periods when the Mainland Chinese markets have significantly lower volatility relative to the Hong Kong and Taiwanese markets. This finding suggests that it is not necessarily true that the emerging markets are always more volatile than the developed markets. Equally important, the Greater China markets apparently share a common degree of volatility persistence, implying fractional integration of the financial markets in the Greater China region.

These findings have various implications for asset allocation and portfolio management. First, volatility asymmetry has implications for the valuation of options and volatility forecasting. Taking asymmetry into account will provide a more realistic measurement of the risk premium associated with a risky portfolio. Second, the dynamic correlations have implications for portfolio management and diversification. As conditional correlations are found to be significantly time-varying for the Greater China stock markets, the weights for a portfolio of assets from these markets have to be adjusted dynamically to achieve optimality in asset allocation. As conditional correlations between the Greater China stock markets have strengthened over the years, there could be diminishing benefit from portfolio diversification. Third, volatility persistence and asymmetry can affect the confidence interval associated with the forecast

of stock market returns. Long-range persistence can also influence portfolio allocation, because optimal portfolio allocations may become extremely sensitive to the investment horizon if the volatility of the returns is highly persistent. Similarly, optimal hedging decisions must take into account long-range dependencies in volatility. Fourth, the volatility disparity between the A-share and B-share markets also has implications for the potential merger of the two markets. To mitigate the increased volatility associated with speculation of the possible merger of the two markets, it may be imperative for the government to engineer a clear plan of merger with a specific timeframe. Finally, the observation of a common long-run component in the volatility processes may prove helpful in the construction of long-term forecast intervals and in the calculation of optimal hedge portfolios. Modern asset pricing theories suggest that the price today is a function of the conditional variance of the future asset returns, or the covariance with some benchmark portfolios. If shocks to the conditional variance or covariance have only temporary effects, the risk premium associated with long-term contracts will not be affected very much. On the other hand, if the conditional variance is persistent, the pricing of long-term contracts will be a nontrivial function of today's information set. At the same time, if the assets in a portfolio are co-persistent in variance with the co-persistent vector proportional to the vector of asset shares, the risk premium for long-term contracts in that portfolio will tend to be time-invariant.

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