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Abstract

This paper explores the linkages between the different stock markets in the Greater China region. Cointegration tests indicate that the three markets are not cointegrated. A vector-autoregressive multivariate conditional volatility model that accounts for asymmetric volatility effects is used to model the mean and volatility processes of the different stock markets. The empirical findings indicate spillover effects in both mean and variance between the markets. Both China and Hong Kong are affected by mean spillover effects from Taiwan, while Hong Kong and Taiwan show signs of a feedback relationship in their volatility processes. The latter markets also show clear signs of asymmetric volatility effects, while China's market seems to follow a symmetric volatility path. Overall, the Mainland China market is much less interdependent with the other two markets, whereas Taiwan and Hong Kong show clear bidirectional spillover effects. Furthermore, the volatility persistence is strong in all three markets, and especially so in the Mainland China stock market, where the half-life of innovations in the volatility process is close to 40 periods.

Keywords: Stock markets; Greater China; Cointegration; Causality; Multivariate EGARCH; Volatility Spillovers

JEL Classification: C22; F31; F36; G15

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1 Introduction

As the economic growth continues at an unprecedented level, stock markets in the Greater China region (Mainland China, Hong Kong and Taiwan) are attracting the interest of international investors. Even though the Hong Kong and Taiwan stock markets have existed for a long time, it was not until in the end of 1990 that the first stock exchange was formally established in Mainland China. Empirical studies on emerging markets in general indicate that they are becoming more integrated with the rest of the world over time. At the same time, it has been noted that emerging markets may not be as efficient as more developed stock markets. Bekaert (1995) demonstrates that returns in emerging markets exhibit a higher level of autocorrelation compared to returns in industrialized countries, indicating that emerging markets may be more predictable.

Common factors seem to affect different stock markets around the world. For instance, Campbell and Hamao (1992) identify integration between the U.S. and Japanese financial markets. Booth *et al.* (1997) show that the Scandinavian markets exhibit some interdependency in both mean and volatility. At the same time, it is evident that local events and information have a significant impact on the development in the local stock market (Aggarwal *et al.*, 1999). Harvey's (1995) results indicate that emerging markets may be more likely than developed markets to be influenced by local events. It is therefore of interest to look at whether emerging markets in different regions are affected by each other, or whether they mainly respond to domestic news and shocks.

The main novelty in this paper is the application of multivariate volatility analysis to the markets in the Greater China region. Very few studies have focused on the three markets in this region, and to our knowledge, none of them have applied multivariate volatility models that incorporate possible volatility spillover effects to shed light on the dynamic relationship between the markets. Using multivariate GARCH models that takes into account the possibility of asymmetric volatility effects enables us to better understand the interdependence among the markets in the region. The rest of the paper is organized as follows: section 2 provides a brief overview of literature related to the three stock markets and work on financial markets that utilizes multivariate volatility models. Section 3 describes the data including unit root and cointegration tests. Section 4 describes the methodology and section 5 presents the empirical results. Finally, section 6 summarizes the main conclusions.

2 Literature Review

Much work has been done on stock market integration in the Asian region. For instance, Chan *et al.* (1992) study possible cointegration among the so-called Four Little Dragons, i.e. South Korea, Taiwan, Hong Kong, and Singapore. Similarly, Chowdhury (1994) looks at these four countries together with the stock markets in Japan and the U.S. in order to determine their relative importance to the smaller Asian markets. Masih and Masih (1997) also apply cointegration tests to the four Asian stock markets and test whether these are cointegrated with four developed stock markets (the U.S., German, Japanese, and U.K. markets). An interesting study by Ghosh *et al.* (1999) indicates that some of the Asian stock markets are closer to the Japanese market, while others are more linked to the U.S. market. Darrat and Zhong (2002) test for cointegration between different Asian countries, the U.S. and Japan. Similarly, Sharma and Wongbangpo (2002) study the relationship between different Asian stock markets by applying cointegration tests. Johnson and Soenen (2002) look at possible co-movements between twelve Asian stock markets.

Although a lot of previous work has been done on the Asian stock markets, very few articles focus on the Greater China region. With the continuous growth of the economy in Mainland China, the handover of Hong Kong to China in 1997, and Taiwan's growing economic ties to the mainland, it is clear that the Greater China region is becoming an important player in the global financial markets. We therefore believe that it is important to study the relationship between the different stock markets in the region. As mentioned, to our knowledge there are very few studies on this issue. Cheng and Glascock (2005) find that the three markets in the region are not cointegrated with the larger markets in Japan or the U.S., but that weak nonlinear relationships exist between the markets in the Greater China region. They test for cointegration and innovation accounting. They also apply a bivariate test developed by Okunev and Wilson (1997) to look for nonlinear relationships between the different markets. They find that the markets in the region are not cointegrated. Moreover, Wang and Firth (2003) use a simplified procedure to study possible mean and volatility spillovers between the markets in Greater China and the markets in Japan, the U.S., and the U.K. They first apply univariate GARCH models and then use the results to test for mean and volatility spillover in intra-day data. Finally, Zhu *et al.* (2004) use standard cointegration and Granger causality tests in order to identify possible dependencies between the Shanghai, Shenzhen and Hong Kong stock markets. They find a positive feedback relationship between the two Mainland China stock markets and that Hong Kong Granger-caused Shanghai and Shenzhen. In this paper, we apply a multivariate volatility model that allows for simultaneous estimation of both mean and volatility spillover effects and the existence of asymmetry in volatilities.

3 Data, Unit Roots and Cointegration Tests

3.1 Data and descriptive statistics

Included in this sample study are stock prices for the three main stock markets in the Greater China region covering the period January 5, 1994 to December 31, 2005. Stock prices on the three markets are represented by indices: the Hang Seng Index (Hong Kong), the Dow Jones China 88 (Mainland China, an index that includes the major stocks listed on the Shanghai and Shenzhen stock exchanges), and the Taiwan Weighted Index. We want to avoid possible problems with day-of-the-week effects and non-synchronous trading in daily financial time series. At the same time, using a very wide time span may result in the failure to capture the information content of changes in levels and returns.

The data is therefore sampled weekly. The three different time series are from Datastream and include a total of 626 observations. Before we transform the series into returns, we take a look at the level features in the data. All the data points in the sample are transformed into logarithmic scale and shown in Figure 1. The index levels indicate that the three series are non-stationary, a usual feature in global equity markets. We therefore have to consider the possibility of cointegration between the three variables.

We then compose weekly total stock returns. The rate of change in the data is calculated as continuously compounded returns, or $R_{i,t}=\ln[P_{i,t}/ P_{i,t-1}]*100$, where $R_{i,t}$ denotes the continuously compounded return for index i at time t and $P_{i,t}$ denotes the price level of index i at time t. We end up with 625 observations for the three returns series shown in Figure 2. The graphs strongly indicate that the return series are stationary. Table 1 presents some descriptive statistics for the return series. The means range from -0.0051 to 0.0346 percent, and are all close to zero. The maximum and minimum values together with the variance levels reveal some of the different natures of the three markets. The Hong Kong and Taiwan stock markets show much lower minimum levels (approximately -14 and -11 percent respectively) compared to the Mainland China stock market with a maximum negative return of over 29 percent. Similarly, the maximum are much lower for the former markets, with close to 13 and 12 percent compared to over 36 percent for the Mainland China market. The volatility level for the Mainland China market is also much higher, with a standard deviation of 4.6 compared to 3.5 and 3.6 for the markets in Hong Kong and Taiwan. The measures for skewness indicate that the return series are skewed, albeit in different directions, with the Hong Kong and Taiwan markets being negatively skewed (the most common feature in international stock markets), while the Mainland China market is positively skewed. Also, the excess kurtosis measures show that all three series are leptokurtic. However, the Mainland China stock market show signs of significantly higher levels of excess kurtosis with respect to the normal distribution. The existence of excess kurtosis suggests that the model chosen for the return series should accommodate for this specific characteristic.

Furthermore, the Ljung-Box tests clearly indicate some presence of serial correlation in some of the return series at different lag lengths. More importantly, the Ljung-Box tests on squared returns reveal a strong and siginificant deviation from normality, indicating the presence of ARCH effects. In order to see the presence of volatility clustering clearly, Figure 3 shows the sample autocorrelations for the returns and squared returns. The return series show signs of mild autocorrelations. The sample autocorrelations for the squared return series suggest significant volatility clustering in all four series. These results are thus in favor of a model that incorporates ARCH/GARCH features.

Table 1: Descriptive Statistics for Returns

	China	Hong Kong	Taiwan
Observations	625	625	625
Mean	-0.0051	0.0346	0.0027
Min	-29.2548	-14.2093	-11.6072
Max	36.2865	13.2277	11.7635
Standard Deviation	4.6207	3.4854	3.5709
Skewness	0.8311	-0.4490	-0.1322
	(0.0000)	(0.0000)	(0.0000)
Excess Kurtosis	11.650	1.569	0.804
	(0.0000)	(0.0000)	(0.0000)
LB(4)	4.9808	10.7707	2.2162
	(0.2893)	(0.0293)	(0.6961)
LB(8)	11.9229	12.9777	3.6508
	(0.1547)	(0.1126)	(0.8872)
LB(12)	24.2744	18.3209	8.2874
	(0.0187)	(0.1063)	(0.7623)
$LB^2(4)$	53.3691	54.7157	102.5223
	(0.0000)	(0.0000)	(0.0000)
$LB^2(8)$	77.1928	83.8531	165.0539
	(0.0000)	(0.0000)	(0.0000)
$LB^2(12)$	144.9104	131.9041	202.1147
	(0.0000)	(0.0000)	(0.0000)

Note: Return diagnostics for the three indices (weekly data) over the interval, January 5, 1994, through December 31, 2005. Returns are given by $R_{i,t}$=ln[$P_{i,t}$/ $R_{i,t-1}$]*100. The Ljung-Box Q (LB) tests are for serial correlation in 4, 8, and 12 lags for the returns and squared returns. Figures in parentheses are *p*-values.

Table 2 shows the unconditional correlations for the four series. The Mainland China stock market is weakly correlated with the Hong Kong and Taiwan markets. The Taiwan market exhibits a very low level of correlation with the Mainland China market in both the whole sample and the two subperiods. The relationship between the Hong Kong and Taiwan markets is much stronger, with a correlation coefficient of 0.34 compared to a correlation coefficient 0.07 and 0.04 to the Mainland China stock market. These initial figures indicate that the Mainland China stock market is only weakly related to the other markets in the Greater China region.

Table 2: Unconditional Correlation Coefficients

	China	Hong Kong	Taiwan
China	1.0000		
Hong Kong	0.0749	1.0000	
Taiwan	0.0444	0.3412	1.0000

3.2 Unit Root, cointegration, and asymmetry in volatility tests

That most financial time series are integrated and thus have a unit root is today commonly accepted. To be able to determine whether two or more series are cointegrated, we first have to identify the level of integration in each of the three series. Several tests for unit roots have been proposed[1]. Arguably the most common test is the so-called Augmented Dickey Fuller (ADF) test (Dickey and Fuller, 1979). If the test fails to reject the null hypothesis, the series is said to be non-stationary. ADF tests are commonly used without intercept and trend, with intercept, or with intercept and trend. The ADF assumes that the disturbance term is homogenous. To allow for possible the disturbance to be weakly dependent and heterogeneously distributed, Phillips and Perron (1988) suggested a semi-parametric variant of the ADF test.

We conduct both tests on the three time series. The results of the ADF test with the three different specifications and the PP test with intercept and

[1] See, e.g., Hamilton (1994).

with intercept and trend are presented in Table 3. It is evident that none of the three log-level series are stationary. All of the ADF or PP specifications fail to reject the null hypothesis of non-stationarity. When the tests are carried out on the first difference of the series, all the unit root tests indicate that these are stationary. These results tell us that all three series are integrated of order one, i.e. $I(1)$.

Table 3: Unit Root Tests

	Augmented Dickey-Fuller			Phillips-Perron	
	Constant	Intercept	Int. & trend	Intercept	Int. & trend
Log Level					
China	-0.0422	-1.7897	-1.6557	-1.6783	-1.6385
Hong Kong	0.3430	-2.1169	-2.4617	-2.1581	-2.6154
Taiwan	0.0012	-2.2066	-2.2608	-2.1715	-2.2092
First Difference					
China	-8.4767***	-8.4697***	-8.4954***	-22.9905***	-22.9965***
Hong Kong	-12.3671***	-12.3600***	-12.3645***	-24.5119***	-24.5152***
Taiwan	-12.1473***	-12.1375***	-12.1275***	-24.0666***	-24.0668***

Note: Numbers in the three first columns are ADF t-statistics for testing the null hypothesis of non-stationarity. The Akaike Information Criterion is used to choose the optimal number of lags. Critical values are from MacKinnon (1991).

If two time series are found to be integrated of the same order, one can test for cointegration between them. Since the results of the unit root tests indicated that all three of the stock markets are $I(1)$, we continue with a cointegration test. In general, if $\mathbf{Y}_t$ contains two $I(d)$ series, then a linear combination of the series, $C_t = \alpha \mathbf{Y}_t$, is also $I(d)$. If a vector α exists such that the linear combination is $I(d\text{-}b)$ with $b > 0$, then the series are said to be cointegrated of order $I(d\text{-}b)$. The original test for cointegration tests was presented by Engle and Granger (1987). We use the somewhat more elaborate Johansen methodology (Johansen, 1988, and Johansen and Juselius, 1990). The Johansen methodology is commonly preferred by economists since only one step is involved compared to two steps in the Engle and Granger setup and since it makes it possible to deal with more than two variables. If we assume that the vector $\mathbf{Y}_t$ follows a $VAR(p)$ in levels, then we can write

$$\Delta \mathbf{Y_t} = \alpha + \delta_1 \Delta \mathbf{Y_{t-1}} + \cdots + \delta_{p-1} \Delta \mathbf{Y_{t-p+1}} + \delta_0 \mathbf{Y_{t-1}} + \varepsilon_t \tag{1}$$

where α is a constant and υ_t are the error terms. The Johansen test is basically a unit root test, which means that the parameter of interest is

$$\delta_0 = \mathbf{A}_1 + \mathbf{A}_2 + \ldots + \mathbf{A}_p - \mathbf{I} \tag{2}$$

The Johansen method is thus a test for the number of non-zero eigenvalues of the matrix δ_0. A standard trace test is used for the number r of non-zero eigenvalues. The null hypothesis H_0: $r \leq R$ is tested against H_1: $r > R$. The test statistic is computed as

$$Tr = -T \sum_{i=R+1}^{n} \ln(1 - \hat{\lambda}_i) \tag{3}$$

where T is the sample size, n the number of variables and λ are the real number eigenvalues of Π_0. A test for maximum eigenvalue can also be conducted and will be reported together with the trace test in this paper. If we find a cointegration relationship between the three variables, we need to take this into consideration when we formulate the mean equation in the multivariate EGARCH model. If the three series are cointegrated, we may proceed with an error correction model in the mean equation and analyze the long- and short-run relationships between the variables. If they are not cointegrated, we simply specify the mean equations with a vector-autoregressive model.

The results of the trivariate Johansen cointegration test are presented in Table 4. In this test we used an unrestricted constant in the setup. However, the results are robust for other specifications as well. The results in Table 4 show that there is no cointegration relationship between the three series. This means that there is no specific long-term relationship between them that has to be modeled with an error correction framework. These results support those of Cheng and Glascock (2003), whom did not find any cointegrating relationship between the three markets using weekly data from January 1993 to August 2004. Similarly, Zhu *et al.* (2004) were unable to find any cointegrating relationship between the Shanghai, Shenzhen, and Hong Kong stock markets using daily data from the beginning of 1993 to the end of 2001.

Table 4: Johansen Multivariate Cointegration Tests

Eigenvalue	Null	λ_{max}	λ_{trace}
0.0152	r = 0	9.59	17.96
0.0084	r ≤ 1	5.29	8.37
0.0049	r ≤ 2	3.09	3.09

Note: *, **, and *** denotes significance on the 10%, 5%, and 1% respectively. The lag lengths in the Johansen test procedure were selected based on the Akaike Information Criterion. r denotes the number of cointegrating vectors in the null hypothesis. Johansen's $\lambda_{\max}$ and λ_{trace} values are reported in the table. Critical values are found in Osterwald-Lenum (1992).

Before we move on to specify the model, we need to consider the possibility of asymmetric features in the volatility processes. Numerous studies have shown that many financial time series respond differently to positive and negative shocks. For instance, in some markets, large negative returns tend to be followed by periods of high volatility. This suggests that positive and negative shocks may have asymmetric impacts on future conditional volatility. Black (1976) recognized this feature in market data and suggested that it can be a result of how firms are financed. When the market value of a firm decreases, the debt-equity structure changes, leading to an increase in the debt-to-equity ratio (known as the leverage of the firm). This is known as the 'leverage effect'. Basic GARCH models cannot capture such asymmetric effects, and it is therefore important to first take a closer look at the behavior of the volatility. Engle and Ng (1993) proposed a series of tests for asymmetry in volatility, commonly known as sign and size bias tests. These tests are applied to the residuals of a basic GARCH model of returns data. Four different tests can be carried out:

$$\hat{\varepsilon}_t^2 = \phi_0 + \phi_1 S_{t-1}^- + v_t \tag{4}$$

$$\hat{\varepsilon}_t^2 = \phi_0 + \phi_1 S_{t-1}^- \varepsilon_{t-1} + v_t \tag{5}$$

$$\hat{\varepsilon}_t^2 = \phi_0 + \phi_1 S_{t-1}^+ + v_t \tag{6}$$

$$\hat{\varepsilon}_t^2 = \phi_0 + \phi_1 S_{t-1}^- + \phi_1 S_{t-1}^- \varepsilon_{t-1} + \phi_1 S_{t-1}^+ + v_t \tag{7}$$

S_{t-1}^- is a dummy that takes the value 1 when $\hat{\varepsilon}_t^2 < 0$ and 0 otherwise. The first test shows whether positive and negative shocks impact the conditional variance differently. For the second equation, it is argued that the size of the shock can affect whether the response is asymmetric or not. S_{t-1}^- is then used as a slope dummy variable. If ϕ_1 is significant, negative sign bias is said to be present. In the third test, $S_{t-1}^+ = 1 - S_{t-1}^-$ is a dummy for the positive innovations. The last test is a joint test that asymptotically follows a χ^2 distribution.

When applied to the three markets as reported in Table 5, the asymmetry tests give a mixed picture. The China market does not seem to show any signs of asymmetric effects in the volatility process at all. For the Hong Kong market, only some indication of asymmetry exists, indicating the possible need of nonlinear GARCH models that take such effects into consideration. Finally, the Taiwanese stock market show clear signs of asymmetric features on the conditional volatility process. This means that we have to specify a multivariate GARCH model that explicitly takes this feature into account.

Table 5: Engle & Ng Test for Asymmetry in Volatility

	China	Hong Kong	Taiwan
S^-_{t-1}	-0.1042	0.1307	0.3665***
	(0.2105)	(0.1361)	(0.1223)
$S^-_{t-1}\varepsilon^2_{t-1}$	0.1793	-0.1133	-0.1510
	(0.1970)	(0.1055)	(0.0977)
$S^+_{t-1} = 1\text{-}S^-_{t-1}$	0.0949	-0.2357*	-0.3248***
	(0.1567)	(0.1269)	(0.1109)
Joint χ^2	1.014762	4.0704	10.5120**
	p = 0.7977	p = 0.2540	p = 0.0146

Note: *, **, and *** denotes significance on the 10%, 5%, and 1% respectively.

4 Methodology

Having examined the general features of the time series above, we now model the interest rates in the different countries. Since the descriptive statistics indicated a clear presence of ARCH-effects, a multivariate general autoregressive conditional heteroscedasticity (GARCH) model is used. Taking into account that most financial time series have asymmetric effects and the results of the Engle-Ng test earlier, a model that incorporates such features in the volatility is preferred. We choose to use a multivariate version of Nelson's (1991) exponential GARCH (EGARCH) model. Even though there are several other models that capture the asymmetric volatility effects, including the GJR-GARCH and Quadratic GARCH models, there is evidence in favor of Nelsen's model (see, e.g. Hamilton, 1994). Also, since the conditional variance in the EGARCH model is in log form, one does not have to impose parameter restrictions to ensure non-negativity of conditional variances.

Let $R_{i,t} = \log[P_{i,t} / P_{i,t-1}]$ be the returns on stock i at time t, $P_{i,t}$ the price level of stock i at time t, and $P_{i,t-1}$ the price level of stock i at time t-1 respectively. Furthermore, let Ω_{t-1} be the information set at time t-1, $\mu_{i,t}$ the conditional mean, $\sigma^2_{i,t}$ the conditional variance at time t, $\varepsilon_{i,t}$ the error term at time t, and $\xi_{i,t}$ the standardized residuals, or $\xi_{i,t} = \varepsilon_{i,t} / \sigma_{i,t}$. The Vector-Autoregressive Multivariate Exponential GARCH (VAR-MVEGARCH) model can then be expressed as:

$$R_{i,t}|\mathbf{\Omega}_{t-1} \sim f\left(\mu_{i,t}, \sigma_{i,t}^2\right) \tag{8}$$

$$R_{i,t} = \beta_{i,0} + \sum_{j=1}^{J}\sum_{k=1}^{K} \beta_{i,j} R_{i,t-k} + \varepsilon_{i,t} \tag{9}$$

$$\sigma_{i,t}^2 = \exp\left\{\alpha_{i,0} + \sum_{j=1}^{n} \alpha_{i,j} f_j\left(z_{j,t-1}\right) + \gamma_i \ln\left(\sigma_{i,t-1}^2\right)\right\} \tag{10}$$

$$f_j\left(z_{j,t-1}\right) = \left(\left|z_{j,t-1}\right| - E\left(\left|z_{j,t-1}\right|\right) + \delta_j z_{j,t-1}\right) \tag{11}$$

$$\sigma_{i,j,t} = \rho_{i,j}\sigma_{i,t}\sigma_{j,t} \qquad \text{for all } i, j \text{ and } i \neq j \tag{12}$$

Equation (9) represents the mean equation in the model. In the mean equation, the conditional mean of the return is influenced by its past values as well as the past values of the other conditional returns in a vector autoregressive process. This means that, if a parameter $\beta_{i,j}$ (and $i \neq j$) is significant, there exists a mean spillover from market j to market i.

The conditional variance process is described in (10). It follows an EGARCH process and includes its own past innovations as well as past innovations from the other markets in the model. It also allows for the possible asymmetric feature in the volatility process, a feature that is modeled in (11), where $[z_{i,t-1}|-E(|z_{i,t-1}|)]$ measures the size effect of the innovations and where asymmetry exists if δ_i is negative (for leverage effects) and significant. A convenient way to examine the asymmetry in volatility transmission is by using the derivative of the asymmetry process with respect to δ_i:

$$\frac{\partial f_j(z_{j,t})}{\partial z_{j,t}} = \begin{cases} 1+\delta_j, & \text{for } z_j > 0 \\ -1+\delta_j & \text{for } z_j < 0 \end{cases} \tag{13}$$

This means that when δ_i is negative (positive), a negative $z_{i,t}$ reinforces (mitigates) the size effect. The persistence in volatility is measured by γ_i in (10). If γ_i is smaller than one, then unconditional variance exists. However, if it is equal to one, then it is infinite and can be said to follow an integrated process of order one (see Nelson, 1991).

Looking at the conditional correlation in (12), constant correlation is assumed (see Bollerslev, 1990). Assuming normality of the conditional distribution of the variables, the log-likelihood function of the model can be written as

$$L(\theta) = -\frac{\kappa T}{2}\log(2\pi) - \frac{1}{2}\sum_{t=1}^{T}\left(\log\left|H_t\right| + \varepsilon_t' H_t^{-1}\varepsilon_t\right) \qquad (14)$$

Here, κ is the number of equations, T is the number of observations, and t is the parameter vector that will be estimated. Furthermore, ε_t = [$\varepsilon_{1,t}$, $\varepsilon_{2,t}$, …] is the vector of innovations at time t and H_t is the time-varying conditional variance-covariance matrix. Finally, the nonlinearity in the arguments of the likelihood function in expression (14) means that we need a numerical maximization procedure like the one used in Berndt *et al.* (1974).

5 Empirical Results of the VAR-MVEGARCH

The stock markets in the Greater China region have developed independently from each other. Both the Taiwan and Hong Kong stock markets have a much longer history than the two stock markets on the mainland. At the same time, there are clear linkages between at least the Hong Kong market and the Mainland China market, given that an increasing number of mainland companies chose to go public in Hong Kong in order to attract foreign capital. How do these different issues show in the empirical relationship between the three markets? The results from the VAR-MVEGARCH in Table 6 indicate the presence of spillover effects in both mean and volatility. Looking first at the mean equations, neither China nor Hong Kong's stock markets influence the other markets in the region. However, there are significant spillover effects in the mean from Taiwan to both China and Hong Kong. Given the formal restrictions for Taiwan investors to invest in the mainland and vice versa, this is an interesting result, indicating that there are indeed existing relationships between the different markets. It also indicates that Taiwan is a significant player in the news-generating process.

Looking at the second-order relationships between the three markets, the Mainland China stock market seem to exert very little influence on the other markets in the region. The only indication of influence of China's past innovations is on the Mainland China stock market itself. On the other hand, there are significant volatility spillover effects from Hong Kong to both the Hong Kong stock market itself and the Taiwanese stock market. Past innovations in the Taiwanese stock market also influence subsequent volatility in the same market. An interesting addition to this is feature is that there is a significant volatility spillover effect from the Taiwanese market to the Mainland China stock market. This means that innovations in the Taiwanese stock market spill over into the Mainland Chinese stock market in both the first and second moments.

The parameters for asymmetric effects in volatility (δ_i) are significant in both Hong Kong and Taiwan, a result that goes hand in hand with the preliminary Engle-Ng test for asymmetric volatility earlier. This means that the nature of past news is important ingredients in the volatility spillover process. For Taiwan and to a certain extent Hong Kong, negative innovations increase volatility more than positive innovations and the findings suggest that these stock markets are sensitive to news. Using the derivative in expression (13), we can compute the ratio $|-1+\delta_i|/(1+\delta_i)$. The ratio indicates that bad news for Hong Kong and Taiwan has 1.98 and 6.19 times the impact of good news respectively. This clearly indicates asymmetry in the markets, a phenomenon which is recognized in equity markets around the world.

When it comes to persistence in the volatility process, it is clear that the persistence parameter (γ_i) is significant in all three markets. Furthermore, the parameters for volatility persistence are large, which means that volatility lingers in all of the markets. To get a better understanding of volatility persistence in the three markets, the so-called half-life (HL) can be computed as $HL_i = \ln(0.5)/\ln(\gamma_i)$. The half-life for China, Hong Kong, and Taiwan is 39.7, 21.4, and 15.1 respectively. This means that volatility is very persistent, with half-life ranging from close to 40 weeks down to 15 weeks in the three markets.

To check if asymmetry in the volatility process persists, we conduct a new Engle-Ng test. The results, presented in Table 7, indicate that the MVEGARCH captures the asymmetry effect in a satisfactory way. The pair wise correlation coefficients ($\rho_{i,j}$) match the unconditional coefficients and there is again only a weak correlation between China and Hong Kong as well as between China and Taiwan. The correlation between Taiwan and Hong Kong is much stronger, a natural result given their relatively more open and developed markets.

The results of the correlation coefficients are supported by the conditional volatility processes in Figure 4. It is clear that the volatility in Hong Kong and Taiwan move close together, while the development in the second order moment of the Mainland China market seem to move much more independently, a natural result given that mainland investors have been limited to invest only in mainland assets. However, the limited possibility for mainland investors is certainly changing while at the same time foreign investors' interest for mainland investments is on a steady increase. Overall, the empirical results support the arguments in Harvey (1995). As mentioned earlier, the stock markets in Hong Kong and Taiwan were established much earlier than those in Mainland China and have had more time to integrate with the markets in the rest of the world. Also, the Mainland China market is still experiencing problems with over liquidity and a high level of speculation. Gao (2002) show that the annual average turnover ratio, a commonly used procedure to measure the degree of speculation, was more than 500% between 1994 and 2001. This should be compared to figures in the range of 30-70% for more developed markets.

During that period, Hong Kong had an annual average turnover ratio of 58% and Taiwan that of 252%. However, the study also shows that the speculation level in the Mainland China stock market is decreasing as the markets are maturing. In its early days, the mainland markets were characterized by a very large number of smaller stocks and lacked a nucleus of larger and more stable blue chip companies. As more and more blue chip stocks are listed, this situation will change over time. This suggests that the markets in the Greater China region will most probably exhibit an increasing level of integration in the future.

To conclude, there are significant spillover effects in both mean and variance between the different markets. However, the Mainland China stock market is much less related to the other two markets, as could be expected given their respective history and development.

Table 6: Maximum Likelihood Estimates of the VAR-MVEGARCH

	China (i = 1)	Hong Kong (i = 2)	Taiwan (i = 3)
$\beta_{i,0}$	-0.1488	0.0659	0.0497
	(0.1367)	(0.1230)	(0.1287)
$\beta_{i,1}$	0.0331	-0.0339	0.0041
	(0.0414)	(0.0273)	(0.0246)
$\beta_{i,2}$	-0.0110	0.0148	0.0300
	(0.0472)	-0.0474	(0.0437)
$\beta_{i,3}$	0.0728**	0.0714*	0.0607
	(0.0323)	(0.0393)	(0.0434)
$\alpha_{i,0}$	0.0519***	0.0729***	0.1090***
	(0.0156)	(0.0272)	(0.0324)
$\alpha_{i,1}$	0.1476***	0.0289	0.0402
	(0.0278)	(0.0378)	(0.0355)
$\alpha_{i,2}$	0.0155	0.1940***	0.1346***
	(0.0374)	(0.0390)	(0.0377)
$\alpha_{i,3}$	-0.1099***	0.0151	0.0986***
	(0.0283)	(0.0316)	(0.0304)
γ_i	-0.1369	-0.3287**	-0.7219***
	(0.892)	(0.1414)	(0.1956)
ξ_i	0.9827***	0.9681***	0.9551***
	(0.0053)	(0.0114)	(0.0133)
$\rho_{1,2}$	0.0933**		
	(0.0454)		
$\rho_{1,3}$	0.0485		
	(0.0486)		
$\rho_{2,3}$	0.3351***		
	(0.0382)		
LogL	-4905.3633		

Residual Diagnostics

	China	Hong Kong	Taiwan
Mean	0.0138	0.0026	-0.0077
Variance	1.0135	1.0118	1.0084
Skewness	0.5890***	-0.4324***	-0.1689*
Kurtosis	3.2227***	0.7828	0.1966
KS Normality	0.052**	0.031	0.034
LB(4)	3.0988	6.4730	1.1852
LB(8)	11.3640	10.5646	2.9068
LB(12)	14.8837	13.7634	7.3244
$LB^2(4)$	2.5284	0.6905	1.3698
$LB^2(8)$	3.2679	2.4712	4.5342
$LB^2(12)$	4.0293	4.6703	6.1772

Note: *, **, and *** denotes significance on the 10%, 5%, and 1% respectively. The Kolmogorov-Smirnov (KS) test for normality is tested on the 5% level, where ** indicates non-normality. The Ljung-Box (LB) statistics are for 4, 8, and 12 lags for the residuals and the squared residuals.

Table 7: Engle & Ng Test for Asymmetry in Volatility

	China	Hong Kong	Taiwan
S^{-}_{t-1}	0.0183	-0.0101	0.0901
	(0.1857)	(0.1346)	(0.1197)
$S^{-}_{t-1}\varepsilon^{2}_{t-1}$	0.0274	0.0435	-0.0073
	(0.1678)	(0.1077)	(0.0974)
$S^{+}_{t-1} = 1\text{-}S^{-}_{t-1}$	0.2011	-0.1134	-0.1297
	(0.1416)	(0.1227)	(0.1056)
Joint χ^2	3.3591	2.1754	1.8554
	p = 0.3395	p = 0.5368	p = 0.6029

Note: *, **, and *** denotes significance on the 10%, 5%, and 1% respectively.

6 Conclusion

The economic growth in China over the last decade has led to a rapid development of the domestic financial markets. While the stock markets on the mainland have existed for merely 15 years, the Taiwan and Hong Kong markets can be seen as more mature markets. This paper explores the possible linkages between the three markets in the Greater China region. Initial tests indicate that all three markets are non-stationary and that they do not exhibit any cointegrating relationship. There are asymmetric tendencies in the volatility of both the Hong Kong and Taiwan markets, and therefore a multivariate volatility model that takes this into account is used. The empirical results suggest significant levels of spillover effects in both mean and variance in the region. China and Hong Kong experience spillover effects in the mean from the Taiwan market. There is also a significant feedback relationship in the volatility processes of the Hong Kong and Taiwan stock markets, indicating a clear presence of integration among these markets. While these two markets are related, it is less clear that the Mainland China market is influenced by or influences the other two markets. This results support previous research that indicate that equity market tend to become more integrated as they develop over time. During the period in this study, domestic information clearly seems to be the dominating force in the Mainland China market. Extremely large turnover in the domestic market and high levels of liquidity support this argument.

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Figure 1: Stock Market Indices

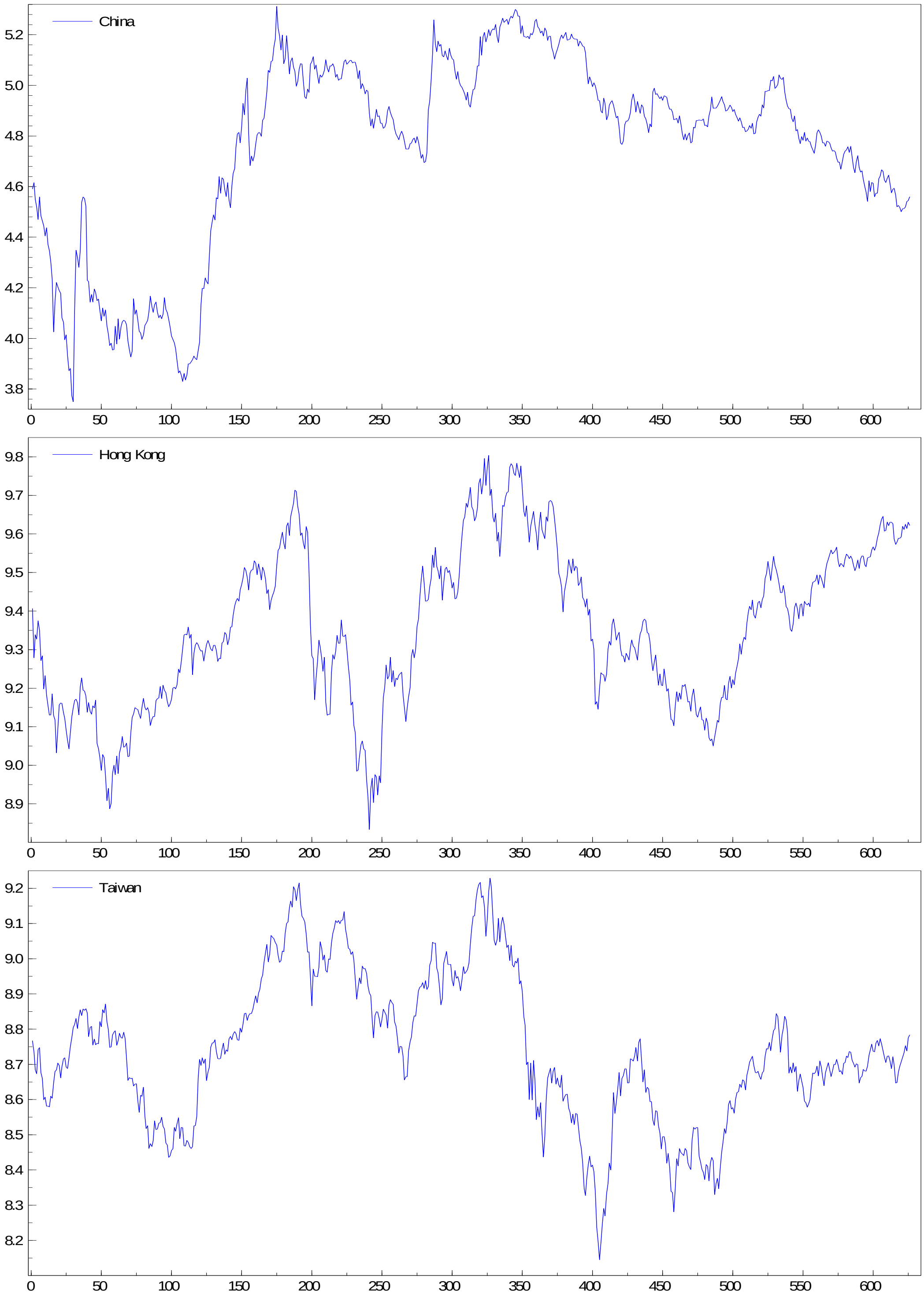

Figure 2: Stock Market Returns

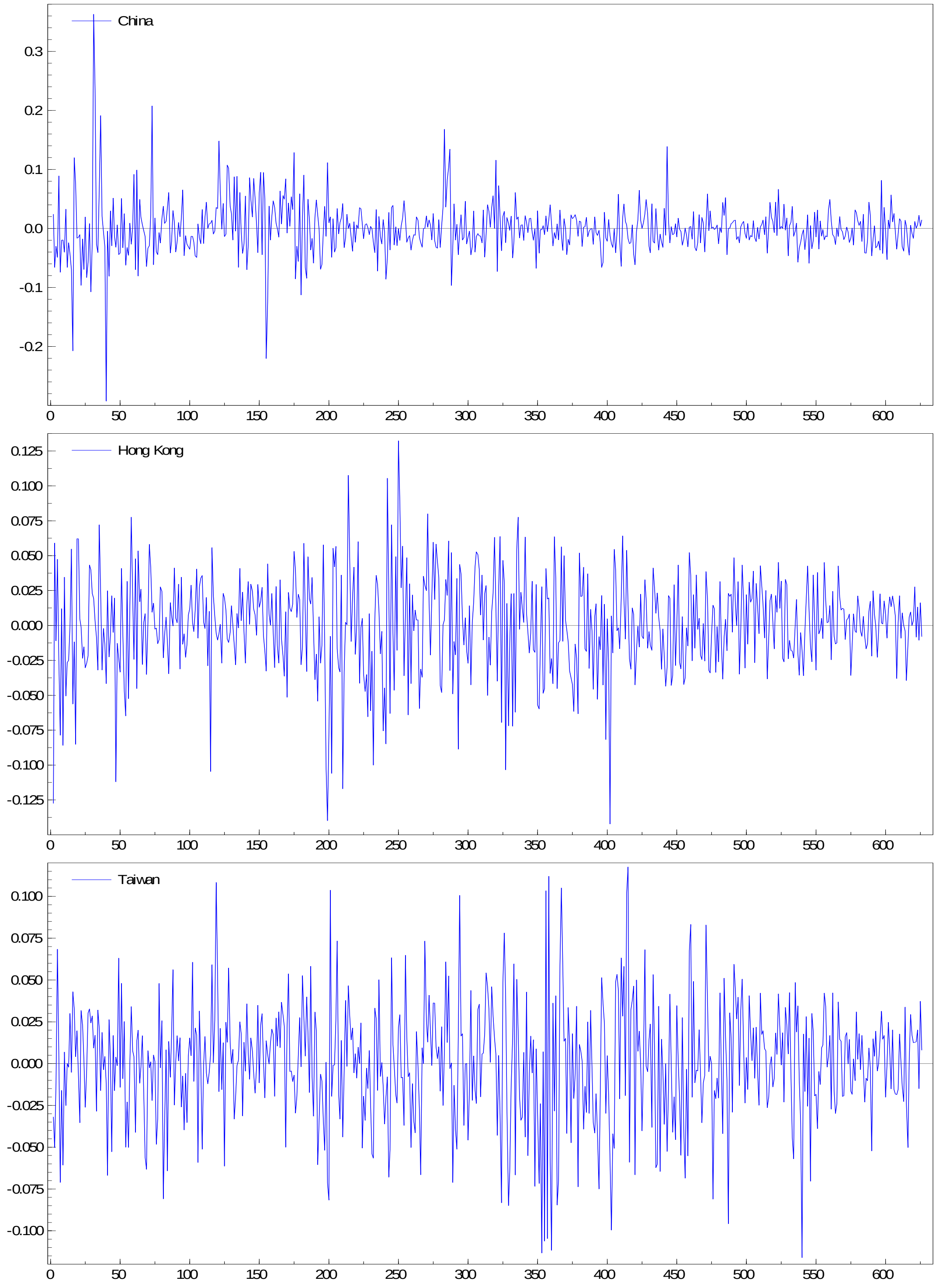

Figure 3: Sample Autocorrelation Functions for Returns and Squared Returns

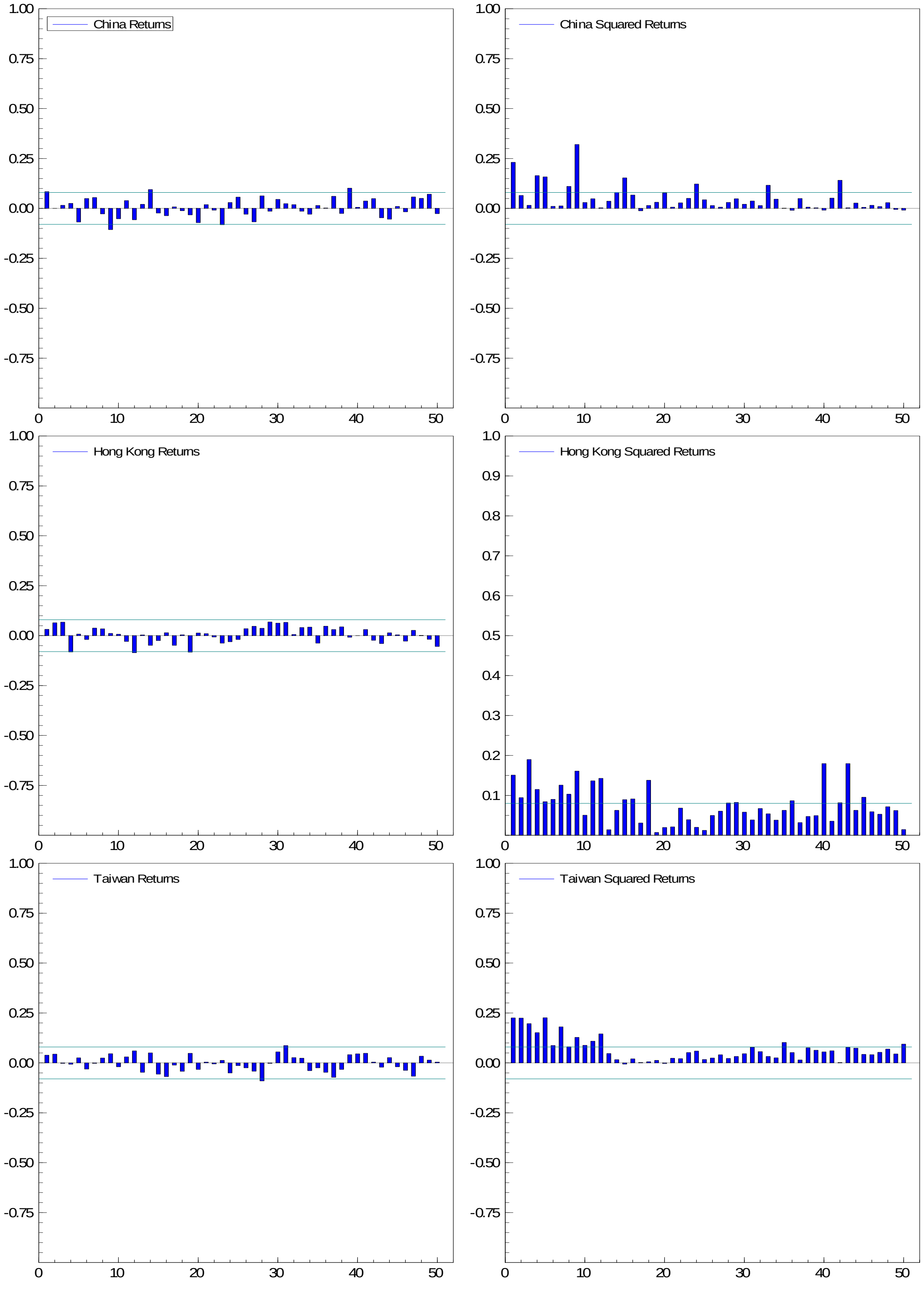

Figure 4: Conditional Volatilities of Returns