Structural Change in Stock Price Volatility of Asian Financial Markets

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Abstract

Structural change in the volatility of five Asian and U.S. stock markets is examined during the post-liberalization period (1990-2005) of Asian financial markets using the Sup-LM test. Four Asian financial markets (Korea, Japan, Hong Kong, and Singapore) experienced structural changes. However, test results do not support the structural changes in volatility for Thailand and the U.S. Also, the empirical results show that the GARCH persistent coefficients tend to increase while the ARCH impact coefficients decrease in Asian markets, which implies that the volatility process has become more persistent.

Keywords : GARCH volatility; persistence; structural change.

JEL classification : C12, C22, C52, G1

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1 Introduction

Generally, Asian financial markets are known to respond predictably to economic events. In particular, important economic events[4] have had comprehensive and indirect effects on the Asian financial markets and the world economy, including risk premiums in the debt market (Allen and Gale, 1999; Allen and Gale, 2000; Bello, 1997; Emmons and Schmid, 2000; Johnson, 1998; Koo, 2003; IMF report, 1998). Ayuso and Blanco (2001) demonstrate that during the 1990's there was a significant increase in the degree of integration among the world stock markets. Many studies have mentioned the potential structural changes with respect to financial market risk in Asian financial markets (Allen and Gale, 1999; Allen and Gale, 2000; Andreou and Ghysels, 2002; Chaudhuri and Klaassen, 2004; Emmons and Schmid, 2000). However, there has not been a comprehensive and in-depth study that addresses and focuses on the potential changes and on the properties of these changes with respect to volatility[5] in the Asian financial markets.

It is important for investors, analysts, and policy makers to predict volatility as they must prepare for the possibility of unexpected price changes. Conceptually, volatility implies the degree of uncertainty (or risk)[6] in price changes, because the value of the volatility will be relatively high (low) when the price of stock experiences huge (small) swings in a short period. Risk is defined as the possibility of an unpleasant event. In many investment cases, volatility can be used to calculate the lower boundary of probability for these events. To analyze the behavior of this volatility, a decomposition of price movements into the expected and unexpected portions of the changes in value can be considered. Since the unexpected change is related to risk and volatility, volatility is useful information in making investment decisions; see Hopper (1996). However, if there is a structural change in the volatility pattern of an economic variable using a given sample period, prediction of volatility from the model without considering the structural change may no longer be consistent and reasonable.

Studies have used various methods to test for possible structural breaks in Asian financial markets. Andreou and Ghysels (2002) use two tests to look for structural changes in volatility for Asian financial markets: one is a

[4]Japan's bubble bursting (early 1990s), the Gulf war (1991), the collapse of the USSR (1991), the Tequila effect in Mexico (1994), the Asian crisis (1997), the world trade center disaster (2001), and outbreaks of Severe Acute Respiratory Syndrome (SARS) (2003).

[5]Volatility is usually referred to as the (annualized) standard deviation of the price return rate. In this study, we refer to volatility as the conditional standard deviation without annualizing, for convenience. See Tsay, 2002, pp. 80.

[6]See Tsay, 2002, pp. 80

CUSUM type test[7], used by Kokoszka and Leipus (2000), and the other is a least squares type test, used by Lavielle and Moulines (2000). Chaudhuri and Klaassen (2004) provide evidence of regime switching due to the Asian financial crisis with respect to volatility patterns in four Asian financial markets: Indonesia, Korea, Malaysia, and Thailand. They use a regime switching method to test for a structural break, but they do not consider detection of a change point in any Asian financial hub (Hong Kong and Singapore). However, Hill (2004) suggests that the Sup LM sup test out-performs other traditional test methods. Smith (2006) provides that the CUSUM tests tend to over-reject, even in quite large samples, when returns have fat tails.

As an alternative method effective for testing structural changes in volatility, Chu (1995) reports a good power of test by employing Supremum (Sup) F and Sup LM tests, which are inspired by Andrews (1993). Along these lines, Smith (2006) finds that the Sup LM test, rather than the CUSUM, improves the power for tests that use artificial data. Also, an empirical study by Smith (2006) detects a structural change in volatility in the S&P 500 in 1989. This type of methodology enables the exposure of multiple structural changes in the case of unknown break point(s) while achieving stronger testing power than that achieved by the CUSUM test. No other studies have addressed the Asian financial markets comprehensively with respect to (multiple) structural change(s) in volatility using the Sup LM test. Further, no one in the financial market literature has addressed the properties of coefficient changes in the GARCH representations. Also, no one has studied change patterns in volatility to examine the existence of (multiple) structural change(s) in volatility.

The objective of this paper is to test for evidence of structural changes in volatility of the Asian financial markets from 1990 to 2005 using the Sup LM test (rather than other test methods used previously) and to detect structural changes if present. The possibility of multiple structural changes will also be investigated. Each of the structural change in volatility points will be determined and incorporated into the study. Moreover, if structural change(s) in volatility exist in any of the financial markets, the main feature of the volatility

[7] Hsu et al. (1974) begin to use this CUSUM test for structural change in volatility. They construct a test based on the alternative probability model of stock return data rather than using a Paretian distribution. Through evidence of non-normality – fat-tail – of the stock return series, they introduce variance as a non-stationary example. Recently, Inclan and Tiao (1994) detected variance changes based on an Iterated Cumulative Sum of Squares (ICSS) algorithm. However, Chihwa and Ross (1995) criticized the standard CUSUM test in Inclan and Tiao (1994) because its performance is quite disappointing. They propose a modified Cumulative Sum of Squares (a modified CUSUM) test for handling serially correlated data. Additionally, Kim, Cho, and Lee (2000) point out that Inclan and Tiao (1994) CUSUM test in GARCH performs appropriately under limited conditions. Kokoszka and Leipus (1999, 2000) develop a theoretical CUMSUM test of variance change in the (G)ARCH model.

structure change will be identified.

2 Empirical Modeling

Generalized Autoregressive Conditional Heteroskedasticity (GARCH), which was developed after the introduction of the Autoregressive Conditional Heteroskedasticity Model (ARCH) by Engle (1982), have been developed as a means to explain the stylized facts of financial variables which show volatility clustering and fat-tailed distribution. Bollerslev (1986) suggests that using GARCH reduces the exploding parameter numbers compared to using the ARCH model (Engle, 1982), and so maintains the parsimonious rule in the econometric model. Using the GARCH model, evidence of structural change in volatility in the Asian financial markets is tested using the Sup-LM test (Andrews, 1993; Chu, 1995; Smith, 2006). In the case of the existence of structural change, change points will be detected using the method developed from Bai (1994, 1997), Yao (1988), and Liu et al. (1997).

Our empirical analysis is based on the following model:

$$y_t = \phi_0 + \sum_{i=1}^{I} \phi_{1i} y_{t-i} + \sum_{j=1}^{J} \phi_{2j} z_{t-j} + u_t \tag{1}$$

$$\sigma_t^2 = \varpi + \alpha u_{t-1}^2 + \beta \sigma_{t-1}^2 + \delta_1 D_t + \delta_2 u_{t-1}^2 D_t + \delta_3 \sigma_{t-1}^2 D_t \tag{2}$$

where D_t is 1 if $t > T^*$ or 0 otherwise, T^* is the possible break point in volatility, and $u_t (= \sigma_t e_t,\ e_t\ iid(0,1))$ and σ_t^2 are the innovation and its conditional variance, respectively.

Our model is composed of the mean equation (1) and the volatility equation (2). The mean equation includes y_t and z_t, which are the log-differenced variables of each stock index and foreign exchange rate, respectively. The foreign exchange rate is considered to account for the relationship between currency depreciation and the stock market as is shown in a number of studies such as Solnik (1987), Ajayi and Mougoue (1996), and Fang (2001,2002)[8].

The volatility equation involves parameters ϖ, α, and β, which are defined, respectively, as a constant coefficient of volatility, an ARCH impact coefficient, implying a short-run adjustment from immediate past shocks, and a GARCH persistence coefficient, implying a relatively long-run pattern of

[8]Based on the empirical results, significance of coefficient ϕ varies on the sample periods. It means that a ϕ is significant in some subsample period, but is insignificant in other periods. Because the significance of ϕ is not our main concern, we did not report.

volatility. Our model involves a dummy variable (D_t) and associated shift parameters (δ_1, δ_2,andδ_3) to allow for structural change in the volatility equation.

For the estimation of the GARCH equation, the quasi-maximum likelihood estimator (QMLE) has been used in many studies. The QMLE assumes that the density of the volatility process follows a normal distribution. Lee and Hansen (1994) and Lumsdaine (1996) have shown that the QMLE of the GARCH parameters are consistent even in the limiting case of integrated GARCH.

When the conditional variance (σ_t^2) is expected by past innovations and past conditional variances, the focus is whether the parameters, $\delta(=(\delta_1, \delta_2, \delta_3))$are zero or not. Because the null hypothesis ($H_0 : \delta = 0$) assumes there is no structural change and the alternative hypothesis ($H_1 : \delta \neq 0$) implies the existence of structural change, the Sup- LM test is parameter stability test in the conditional variance equation. By definition, the possible break point T^* is considered as a fraction τ of the sample size n [9].

Let $\phi = (\phi_0, \phi_{1i}, \phi_{2j})$ and $\theta = (\omega, \alpha, \beta)$. Suppose the likelihood function is given as follows:

$$L_n(\phi, \theta, \delta, \tau) = \sum_{t=1}^{[n\tau]} l_t(\phi, \theta, \delta) + \sum_{t=[n\tau]+1}^{n} l_t(\phi, \theta, \delta) \tag{3}$$

$$where\ l_t(\phi, \theta, \delta) = -\frac{1}{2} ln\sigma_t^2(\phi, \theta, \delta) - \frac{1}{2}\frac{u_t^2(\phi, \theta, \delta)}{\sigma_t^2(\phi, \theta, \delta)}.$$

The score function $g_n(\theta, \tau)$ can be defined using the likelihood function of GARCH:

$$g_n(\phi, \theta, \delta) = \frac{1}{\sqrt{n}} \sum_{t=1}^{[n\tau]} \frac{\partial l_t(\phi, \theta, \delta)}{\partial \delta} \tag{4}$$

[9]Hence, when the dummy variable (D_t) is not considered, the alternative hypothesis can also be expressed by:

$$\begin{aligned} H_{1T}(\pi) : \theta_\tau &= \theta_1\ for\ t = 1, ..., n\tau \\ &= \theta_2\ for\ t = n\tau + 1, ..., n \\ where,\ \theta_1 &\neq \theta_2,\ \theta = (\omega, \alpha, \beta) \end{aligned}$$

$$where\ \frac{\partial l_t(\phi,\theta,\delta)}{\partial \delta} = \left[\frac{\partial l_t(\phi,\theta,\delta)}{\partial \delta_1}, \frac{\partial l_t(\phi,\theta,\delta)}{\partial \delta_2}, \frac{\partial l_t(\phi,\theta,\delta)}{\partial \delta_2}\right]'$$

Under the null hypothesis ($H_0 : \delta = 0$), the restriction renders the likelihood function (3) be the same as the likelihood function without structural change. The standard method of estimating the GARCH model can be applied. We denote $(\widetilde{\phi}, \widetilde{\theta})$as the estimator of the GARCH model without structural change. Thus, the score function, $g_n(\phi,\theta,\delta)$, reduces to the following:

$$\lambda_n(\tau) = \frac{1}{\sqrt{n}} \sum_{t=1}^{[n\tau]} \frac{\partial l_t(\widetilde{\phi}, \widetilde{\theta}, \delta = 0)}{\partial \delta}$$

The information matrix can be defined as follows:

$$Q_n(\tau) = \frac{1}{n} \sum_{t=1}^{[n\tau]} \frac{\partial l_t}{\partial \delta} \frac{\partial l_t}{\partial \delta'}$$
$$= \frac{1}{n} \begin{bmatrix} \sum_{t=1}^{[n\tau]} \frac{1}{\sigma_t^4} \frac{\partial \sigma_t^2}{\partial \delta_1} \frac{\partial \sigma_t^2}{\partial \delta_1}, & \sum_{t=1}^{[n\tau]} \frac{1}{\sigma_t^4} \frac{\partial \sigma_t^2}{\partial \delta_1} \frac{\partial \sigma_t^2}{\partial \delta_2}, & \sum_{t=1}^{[n\tau]} \frac{1}{\sigma_t^4} \frac{\partial \sigma_t^2}{\partial \delta_1} \frac{\partial \sigma_t^2}{\partial \delta_3} \\ \sum_{t=1}^{[n\tau]} \frac{1}{\sigma_t^4} \frac{\partial \sigma_t^2}{\partial \delta_2} \frac{\partial \sigma_t^2}{\partial \delta_1}, & \sum_{t=1}^{[n\tau]} \frac{1}{\sigma_t^4} \frac{\partial \sigma_t^2}{\partial \delta_2} \frac{\partial \sigma_t^2}{\partial \delta_2}, & \sum_{t=1}^{[n\tau]} \frac{1}{\sigma_t^4} \frac{\partial \sigma_t^2}{\partial \delta_2} \frac{\partial \sigma_t^2}{\partial \delta_3} \\ \sum_{t=1}^{[n\tau]} \frac{1}{\sigma_t^4} \frac{\partial \sigma_t^2}{\partial \delta_3} \frac{\partial \sigma_t^2}{\partial \delta_1}, & \sum_{t=1}^{[n\tau]} \frac{1}{\sigma_t^4} \frac{\partial \sigma_t^2}{\partial \delta_3} \frac{\partial \sigma_t^2}{\partial \delta_2}, & \sum_{t=1}^{[n\tau]} \frac{1}{\sigma_t^4} \frac{\partial \sigma_t^2}{\partial \delta_3} \frac{\partial \sigma_t^2}{\partial \delta_3} \end{bmatrix}$$

The LM statistic for the null hypothesis ($H_0 : \delta = 0$) is given by

$$LM_n(\tau) = \lambda_n'(\tau) \cdot V_n(\tau)^{-1} \cdot \lambda_n(\tau) \tag{5}$$

$$where\ V_n(\tau) = V\hat{a}r(\lambda_n(\tau)) = (\hat{k} - 1) \cdot \tau \cdot Q_n(\tau)\ and\ \hat{k} = \frac{1}{n} \sum_{t=1}^{n} \frac{u_t^4(\widetilde{\phi}, \widetilde{\theta})}{\sigma_t^4(\widetilde{\phi}, \widetilde{\theta})}.$$

Then, $\lambda_n(\tau)$ weakly converges to the following form of the Brownian Bridge:

$$\lambda_n(\tau) \Rightarrow \; W(\tau) - \tau \cdot W(1)$$
$$\Big(= (k-1)^{1/2} Q^{1/2} [B(\tau) - \tau \cdot B(1)]\Big)$$

where k, $W(\cdot)$ and $B(\cdot)$ are kurtosis, Wiener process and standard Brownian motion respectively. This is due to the following three asymptotic results,

$$(1)\ Q_n(\tau) \xrightarrow{p} \; \tau \cdot Q \ where,\ Q = E\left[\frac{\partial l_t}{\partial \theta}\frac{\partial l_t}{\partial \theta'}\right]$$
$$(2)\ V_n(\tau) = V\hat{a}r(\lambda_n(\tau)) = (\hat{k}-1)\cdot Q_n(\tau) \xrightarrow{p} V(\tau) = \; (k-1)\cdot \tau \cdot Q$$
$$(3)\ W(\tau) = B(\tau \cdot (k-1) \cdot Q)$$

The Lagrangian Multiplier (LM) statistic has a limiting distribution as follows:

$$LM_n(\tau) = \lambda_n'(\tau) \cdot V_n(\tau)^{-1} \cdot \lambda_n(\tau) \qquad (6)$$
$$\Rightarrow \lambda'(\tau) \cdot V(\tau)^{-1} \cdot \lambda(\tau)$$

$$where,\ \lambda(\tau) = (k-1)^{1/2} Q^{1/2} [B(\tau) - \tau \cdot B(1)] \ and\ V(\tau) = (k-1) \cdot \tau \cdot Q$$

In this study, the Supremum LM (Sup-LM) is applied to test for structural change in volatility with unknown point(s) in the portion $[\underline{\tau}, \overline{\tau}(= 1-\tau)]$ with $\underline{\tau}$=0.15, out of the total sample size (Andrews, 1993).

$$Sup\ LM = MAX_{\tau \in [\underline{\tau}, \overline{\tau}]}\ LM_n(\tau) \qquad (7)$$

Andrews (1993) and Andrews & Ploberger (1994) show that the testing problem is nonstandard because every possible break point should be considered as a nuisance parameter in the case of an unknown break point. Hence, instability of coefficients in the conditional variance equation is tested to find significant evidence of structural change in the volatility structure. Andrews (1993) provides critical values where $p = 3$ for 10%, 5% and 1% significance levels.

For change point ($T^* = \tau^* \times n$) detection, the value of log likelihood obtained from a joint estimation of equations (1) and (2) is applied. The idea is taken from minimizing the Sum of Squares Error (SSE) in Bai (1994, 1997), and using the Schwarz loss in Yao (1988) and Liu et al. (1997). A maximizing likelihood value in the estimation of GARCH does not imply minimizing SSE because GARCH is not a homoskedastic model. In this case, the detection for break points is to find the point that maximizes the log-likelihood rather than to find the point that minimizes SSE or the Schwarz criterion function. If the null hypothesis of the Sup LM test is rejected, it supports the existence of structural change in volatility. In this case, we will find the break point having the highest likelihood value in a sample portion $[\underline{t}, \overline{t}]$, where $\underline{t} = [n\underline{\tau}]$ and $\overline{t} = [n\overline{\tau}]$. Hence, the break point is expressed by

$$T^* = arg \max_{t^* \in [\underline{t}, \overline{t}]} \left(\max_{\phi, \theta, \delta} \ L_n(\phi, \theta, t^*, \delta) \right) \tag{8}$$

After the first structural change point is detected, the existence of multiple breaks is tested by repeatedly applying the above procedures-Sup LM test and then detection of the change point-over all sub-sample groups is investigated.

3 Data

Six stock indices are used: the Hong Kong Hangseng index, the Japan Nikkei 500 index, the Korea KOSPI, the Singapore Straits Times, the Thailand Bangkok SET index, and the U.S. S&P 500 index. The reason for including the U.S. financial market is to compare the volatility parameters between the Asian and the U.S. stock markets. Also, for each Asian market, a foreign exchange rate–each currency against the United States dollar–is used as an explanatory variable for stock price movements. Data are compiled daily from January 1, 1990 to December 31, 2005. All stock indices and exchange rates are transformed to logarithms. Based on the ADF unit root test, all stock indices and foreign exchange rates considered in the paper are found non-stationary. They become stationary after taking the first difference of the variables.

4 Empirical Results

4.1 Tests for Structural Change

Table 1 shows the tests for structural change in the volatility process and the associated break point estimates. The Sup-LM statistic is computed for the sample period January 1, 1990 to December 31, 2005. If the test statistic is significant, then the break point is estimated by maximizing the log-likelihood function. This procedure continues for the sub-sample periods as long as the testing result indicates instability in the volatility equation. The tests for structural change are performed using the GARCH(1,1) model with an autoregressive type mean equation. The AR lag length of the mean equation chosen by the BIC is two for Thailand's market and one for all other financial markets.

All Asian stock markets except Thailand's exhibit structural changes in volatility. The Sup-LM statistics are significant for the financial markets of Hong Kong, Japan, Korea, and Singapore, but the null hypothesis of no structural change maintains for the financial markets of Thailand and the U.S.

After finding the evidence of structural change, the break point that maximizes the likelihood function with structural change in the volatility equation is estimated sequentially using principle (8). From all structural change points shown in Table 1, the entire period can be segmented roughly into three phases of sub-samples. The first phase includes the Gulf War (1990-1991), Japan's economic recession from 1992 (Suzuki, 1997), and corresponding policy changes. The second phase includes the period showing chaos in financial markets due to the Asian financial crisis (in the mid-1990s). The last sample group (the first half of 2000s) represents the recovery period for the Asian financial markets. Figure 1 shows the sequence of realized stock return volatility, and Figure 2 shows the sequence of forecasted stock return volatility computed from the GARCH model and parameter estimates for the sub-sample periods.

Hong Kong has experienced structural changes in volatility three times since 1990. The break dates are detected on November 2, 1993, July 31, 1996, and December 30, 1997. A possible reason for the first structural change can be related to the monetary policy change. The Hong Kong Monetary Authority was founded on April 1993 in Hong Kong through a consolidation of the Office of the Exchange Fund and Office of the Commissioner of Banking. The HK Monetary Authority has played a significant role in maintaining foreign exchange rates, managing foreign reserves, keeping the banking system safe, and constructing the financial infrastructure. The second (July 31, 1996) and third break date (December 30, 1997) correspond to the period of the Asian financial crisis and corresponding policy changes. After mid-1997, the currency value in Hong Kong dropped and the stock market became more volatile. The HK Monetary Authority raised overnight rates from 8% to 23% on August 15, 1997, and adopted the policy of a pegged currency based on sufficient foreign reserves (more than $80 billion) in October 1997 to maintain its currency value effectively. Also, the financial market in Hong Kong increased its transparency and competitiveness in June 2000 by initiating the Hong Kong Exchanges and Clearing (HKEX), which is the holding company of the Stock Exchange of Hong Kong Limited[10]. The HKMA announced that the final phase of interest rate deregulation covering Hong Kong's dollar savings and current accounts

[10]Hong Kong Futures Exchange Limited and Hong Kong Securities Clearing Company Limited.

was put in force starting July 3, 2001, allowing interest rates to be determined by the market. These deregulation policies in Hong Kong's financial market appear to have reduced uncertainty and risk dramatically, as Figure 1 and Figure 2 indicate.

Japan, the second largest economy in the world, experienced structural change in stock market volatility on October 6, 1992. One possible reason for structural change can be attributed to the slowdown in economic growth in the 1990s after the economic bubble burst due to excess investment in the stock and real estate markets during the 1980s. Suzuki (1997) reports that Japan's financial system and markets suffered from both instability and inefficiency when the economy plunged into a prolonged balance-sheet recession triggered by the bursting of asset price bubbles[11]. Moreover, the results imply that the Asian crisis had an insignificant impact on the volatility structure of Japan's financial market.

Korea experienced structural changes in volatility twice: the first on December 16, 1994 and the other on June 28, 1996. During the first half of the 1990s, Korea's economic growth rate slowed and the balance of payments showed a growing deficit. Managerial conditions in enterprises were deteriorating, as shown by the lower normal operating profit rate[12]. In addition to these problems, international affairs (the Gulf war, Japan's bubble economy) had a significant effect on predicting the structure of volatility. After President Kim announced a five-year financial sector reform program in June 1993 (primarily for financial liberalization) and confirmed this reform announcement in late 1993, those policies acted as positive signals in the Korean financial market by removing uncertainty. This was effective during the period between the two structural change points. However, prior to the subsequent bankruptcies in Korea at the end of 1996 and early 1997, the second structural change point (June 28, 1996) occurred. Even if the Korean financial market was influenced by speculative attacks in 1997, the market showed evidence of a steady recovery, as noted by successful repayment of the IMF loans, return to a positive balance of payments and continuous economic reform. That is, uncertainty and risk in the Korean financial market have been reduced gradually rather than through a significant jump.

Singapore experienced structural changes in volatility on March 20, 1991, August 7, 1997, and January 29, 2004. After the Singapore financial market had its first change point resulting from uncertainty stemming from the Gulf war and the Latin American crisis in the early 1990s, the market was relatively calm until the Asian crisis in 1997. Guan (2002) suggested that several international shocks, including the Gulf War and the Asian crisis, affected the

[11] Fundamentally, they arise from a bad loans and banking system, under a low interest rate. For detail explanation, see Suzuki (1997).

[12] See Korea Labor & Society Institute (2001).

Singapore economy. In this test, Singapore's economy appeared not to be vulnerable to the event, showing instantaneous recovery from the Asian crisis with a high economic growth rate (9% in 2000), but volatility in Singapore's financial market still existed due to remaining uncertainty, risk, economic recession in 2001, slowdown in the worldwide economy in the beginning of 2000, and the effect of the Severe Acute Respiratory Syndrome (SARS) crisis in 2003. The Singapore market recovered in 2004, as shown by its economic expansion with its major traders: the U.S., EU, China, and Japan. Also, recovery was accelerated when the United States-Singapore Free Trade Agreement became effective[13] at the beginning of 2004. This caused the third structural change (January 29, 2004).

The test results show that Thailand's financial market has had no structural break in volatility since 1990. It is widely accepted that the Asian crisis started in Thailand's financial market. However, the null hypothesis for the Sup LM test that imposes no structural change in volatility over the entire sample size (January 1,1990 - December 31, 2005) cannot be rejected. Also, the persistently fickle behavior of Thailand's volatility, as shown in Figure 1 and Figure 2, supports the empirical results of the Sup LM test.

The U.S. shows no evidence of a structural break in volatility using the Sup LM test because the derived statistic is 7.3533, which is less than the 90% critical value. Figure 1 and Figure 2 also supports this empirical result.

4.2 Estimation

After detecting the change point(s), the GARCH model is estimated again over the sub-sample periods, which are defined using the structural change point(s) found. Table 2 shows the estimation results of the GARCH model in the six financial markets, the five Asian countries and the U.S. The sub-sample periods are defined using the break points estimated in Table 1. The parameter values satisfy the conditions for weak stationary ($\alpha + \beta < 1$).

Table 2 shows the results of the GARCH(1,1) estimations using the entire sample and the sub-samples. The markets which experience structural change(s) (Hong Kong, Japan, Korea, and Singapore) have shown a decreasing ϖ(constant coefficient of volatility), decreasing α(ARCH impact coefficient), and increasing β(GARCH persistence coefficient) since 1990. Hong Kong, Japan, Korea, and Singapore show decreasing ϖ values from 0.0000478 to 0.0000006, from 0.0000092 to 0.0000026, from 0.0000210 to 0.0000018, and from 0.0000278 to 0.0000040, respectively. Also, the parameter values of α have decreased from 0.2502 to 0.0474, from 0.2277 to 0.0934, from 0.1454 to

[13] This free trade agreements is in force with ten economies–Australia, Brunei, Chile, European Free Trade Association, India, Japan, Jordan, Korea, New Zealand, United States–as of 2006.

0.0551, and from 0.2703 to 0.0894, respectively. However, the GARCH persistence coefficient, β, increased from 0.4413 to 0.9500 in Hong Kong, from 0.7559 to 0.8901 in Japan, from 0.7707 to 0.9428 in Korea, and from 0.5973 to 0.8177 in Singapore. These results indicate that the volatility of the Asian stock markets becomes more persistent while the short-run response in volatility becomes weak[14].

Next, we compare the predictive accuracy of two different volatility models, the GARCH models with and without structural change in volatility. The RMSE (Root Mean Square Error) and MAE (Mean Absolute Error) are calculated in four stock markets which have experienced more than one structural change in volatility. Those are based on the difference between the realized volatility of stock return rates and the predicted values of the GARCH model. As Table 3 shows, the forecasts based on the GARCH volatilities with structural change(s) in volatility generate values for RMSE and MAE that are less than those of the GARCH model without structural change(s) in volatility.

5 Conclusions

This paper tests for the stability of volatility processes in selected stock markets (Hong Kong, Japan, Korea, Singapore, Thailand, and the U.S.) for the period 1990-2005. Among those, four stock markets (Hong Kong, Japan, Korea, and Singapore) show one or more structural change in volatility. Those markets all show a structural change in volatility during the first half of the 1990s, mainly due to the Gulf war, Japan's economic recession, and corresponding policy changes. Three markets including Hong Kong, Korea, and Singapore showed additional structural change around the period of the Asian financial crisis in the mid-1990s. The empirical results reveal that Hong Kong and Singapore recovered from the Asian crisis shock more quickly and systematically compared to Korea, which underwent a continual but relatively slow recovery.

However, the results show no evidence of structural change in volatility

[14]Because the Sup LM tests a statistical difference of each coefficient (ϖ ,α , β) in two different adjacent subsample periods, the simple comparison between coefficients may not guarantee a statistical inequality of coefficients between two different subsample periods which are not adjacent. This problem can arise when each coefficient has a trend but fluctuate. The case is similar with our case. Hence, we report the standard errors of coefficients in conditional variance equations in Table 2. When comparing the confidence intervals(=coefficient value $\pm 2(\approx 2)^*$standard error, 95%) of each coefficient (ϖ , α , β) between the first and the last subsample periods in each country, our finding is supported in all coefficients at the 95% confidence interval, except β in Singapore.

since 1990 in the markets of Thailand and the U.S.. In particular, the volatility pattern in the U.S. stock returns is the most stable with the lowest volatility values compared to the Asian financial markets. While Thailand's stock market shows no structural change in volatility after 1990, the main cause seems to be different from that of the U.S. market. Volatility in Thailand's stock market increases steadily with large fluctuations over the sample period. Different from other markets, the Thailand stock market at the end of 2005 had not yet recovered from the Asian crisis. In terms of value, the Thailand stock market is 0.9% that of the US market, 3.2% that of Japan, 13.4% that of Hong Kong, 29% that of Korea, and 53.1% that of Singapore, at the end of 2004. Hence, the immaturity of the Thailand stock market makes it difficult to detect the impact from economic events.

Consequently, after financial liberalization, most Asian countries experienced structural change in their GARCH volatility. In particular, the ARCH impact coefficient, implying a short-run response from immediate past shock, tends to decrease. A GARCH persistence coefficient, implying a relatively long-run pattern of volatility tends to increase over time. These change patterns in the coefficients might be related to the development of financial markets; with each financial market depending more on its past persistent volatilities, rather than past surprises. A multivariate study is needed to confirm such structural interpretations.

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Appendix

Table 1. Structural change test and point detection

Market	Sup LM Test statistics		Break point (mm/dd/yyyy)	Test period (mm/dd/yyyy)
Hong Kong	15.4292**	Break1	11/2/1993	All sample period
	12.1665*	Break2	7/31/1996	11/3/1993-12/31/2005
	19.3983***	Break3	12/30/1997	8/1/1996-12/31/2005
Japan	21.5729***	Break1	10/6/1992	All sample period
Korea	20.4824***	Break2	6/28/1996	All sample period
	13.8127*	Break1	2/16/1994	1/1/1990-6/28/1996
Singapore	15.2850**	Break2	8/7/1997	All sample period
	12.5996*	Break1	3/20/1991	1/1/1990-8/7/1997
	15.1068**	Break3	1/29/2004	8/11/1997-12/31/2005
Thailand	11.03174		-	All sample period
United States	7.3533		-	All sample period

Notes: *, **, and *** indicate that null hypothesis is rejected in 10% 5%, and 1% significant level, respectively. All sample period indicates from 1/1/1990 to 12/31/2005.

Table 2. Coefficients in volatility equations

Sample Period	ϖ [a]	α [a]	β [a]	$\overline{\sigma}$ [b]	Kurtosis
Hong Kong					
All sample period[c]	0.0000034*** (0.0000003)	0.0785*** (0.0005)	0.9079*** (0.0058)	0.0158	7.61
1/1/1990–11/2/1993	0.0000478*** (0.0000065)	0.2502*** (0.0313)	0.4413*** (0.0632)	0.0125	15.78
11/3/1993–7/31/1996	0.0000030*** (0.0000009)	0.0654*** (0.0145)	0.9191*** (0.0156)	0.0141	6.20
8/1/1996–12/30/1997	0.0000115** (0.0000047)	0.1824*** (0.0391)	0.7810*** (0.0436)	0.0177	4.80
12/31/1997–12/31/2005	0.0000006*** (0.0000002)	0.0473*** (0.0055)	0.9499*** (0.0057)	0.0146	4.55
Japan					
All sample period	0.0000037*** (0.0000004)	0.1217*** (0.0077)	0.8597*** (0.0085)	0.0141	4.70
1/1/1990–10/6/1992	0.0000092*** (0.0000029)	0.2277*** (0.0256)	0.7559*** (0.0252)	0.0237	5.35
10/7/1992–12/31/2005	0.0000026*** (0.0000003)	0.0934*** (0.0075)	0.8901*** (0.0086)	0.0126	4.56
Korea					
All sample period	0.0000030*** (0.0000005)	0.0793*** (0.0055)	0.9142*** (0.0056)	0.0215	5.11
1/1/1990–2/16/1994	0.0000210*** (0.0000037)	0.1454*** (0.0184)	0.7707*** (0.0232)	0.0158	4.60
2/17/1994–6/28/1996	0.0000185 (0.0000132)	0.0437* (0.0237)	0.7791*** (0.1335)	0.0102	3.22
7/1/1996–12/31/2005	0.0000018*** (0.0000005)	0.0551*** (0.0057)	0.9428*** (0.0054)	0.0293	5.69

Notes:*, **, and *** indicate that null hypothesis is rejected in 10% 5%, and 1% significant level, respectively. The parenthesis shows a standard error.

$a : \alpha_t^2 = \varpi + \alpha u_{t-1}^2 + \beta\sigma_{t-1}^2.$

$b : \overline{\sigma}$ *is unconditional standard deviation* $(\overline{\sigma} = \sqrt{\omega/(1-\alpha-\beta)})$.

c : *All sample period indicates from* 1/1/1990 *to* 12/31/2005.

Table 2. Coefficients in volatility equations (continue)

Sample Period	ϖ [a]	α [a]	β [a]	$\overline{\sigma}$ [b]	Kurtosis
Singapore					
All sample period	0.0000035*** (0.0000003)	0.1372*** (0.0061)	0.8477*** (0.0049)	0.0152	6.91
1/1/1990-3/20/1991	0.0000278*** (0.0000085)	0.2703*** (0.0567)	0.5973*** (0.0873)	0.0145	12.31
3/21/1991-8/7/1997	0.0000146*** (0.0000025)	0.2049*** (0.0216)	0.6132*** (0.0469)	0.0090	4.93
8/10/1997-1/29/2004	0.0000096*** (0.0000009)	0.1120*** (0.0107)	0.8530*** (0.0084)	0.0166	8.13
1/30/2004-12/31/2005	0.0000040** (0.0000019)	0.0894*** (0.0318)	0.8177*** (0.0692)	0.0066	2.72
Thailand					
All sample period	0.0000052*** (0.0000006)	0.1120*** (0.0063)	0.8746*** (0.0059)	0.0197	4.94
U.S.					
All sample period	0.0000004*** (0.0000001)	0.0532*** (0.0040)	0.9425*** (0.0042)	0.0096	4.97

Notes:*, **, and *** indicate that null hypothesis is rejected in 10% 5%, and 1% significant level, respectively. The parenthesis shows a standard error.

$a : \alpha_t^2 = \varpi + \alpha u_{t-1}^2 + \beta\sigma_{t-1}^2.$

$b : \overline{\sigma}$ *is unconditional standard deviation* $(\overline{\sigma} = \sqrt{\omega/(1-\alpha-\beta)})$.

c : *All sample period indicates from* 1/1/1990 *to* 12/31/2005.

Table 3. RMSE and MAE of GARCH volatilities

	RMSE		MAE	
	GARCH (w s.c)	GARCH (w/o s.c)	GARCH (w s.c)	GARCH (w/o s.c)
Hong Kong	0.01156	0.01175	0.00873	0.00888
Japan	0.00911	0.00914	0.00710	0.00713
Korea	0.01377	0.01388	0.01063	0.01077
Singapore	0.00936	0.00954	0.00677	0.00693

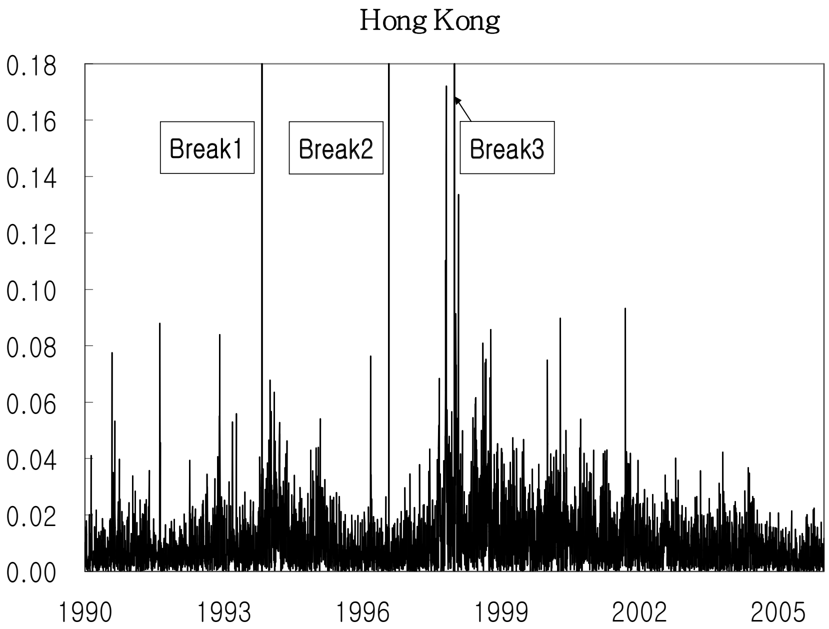
Note:
1.“GARCH(w s.c)” model imposes the structural change in volatility, and GARCH(w/o s.c) model ignores the existence of the structural change in volatility.
2.RMSE (Root Mean Square Error) and MAE (Mean Absolute Error) are defined as follows:

$$RMSE = \sqrt{\frac{\sum_{t=1}^{T}(v_t^r - v_t^g)^2}{T}}$$

$$MAE = \frac{1}{T}\sum_{t=1}^{T}|v_t^r - v_t^g|$$

where, $v_t^r (= stdev[(r_t - \underline{r})])$ is defined as a realized volatility of stock return at time $t(r_t)$. And v_t^g is a GARCH volatility, a conditional standard deviation.

Figure 1. Graphs of realized volatility by market



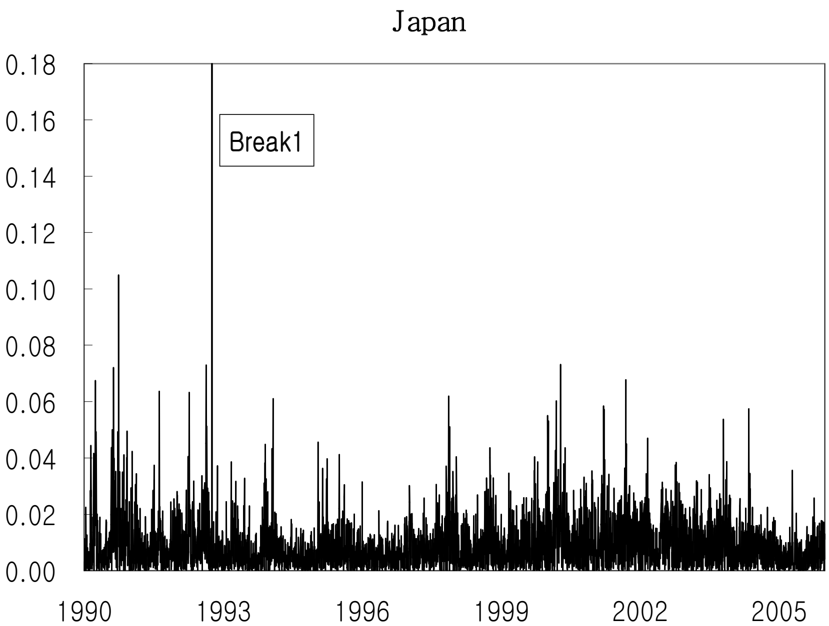
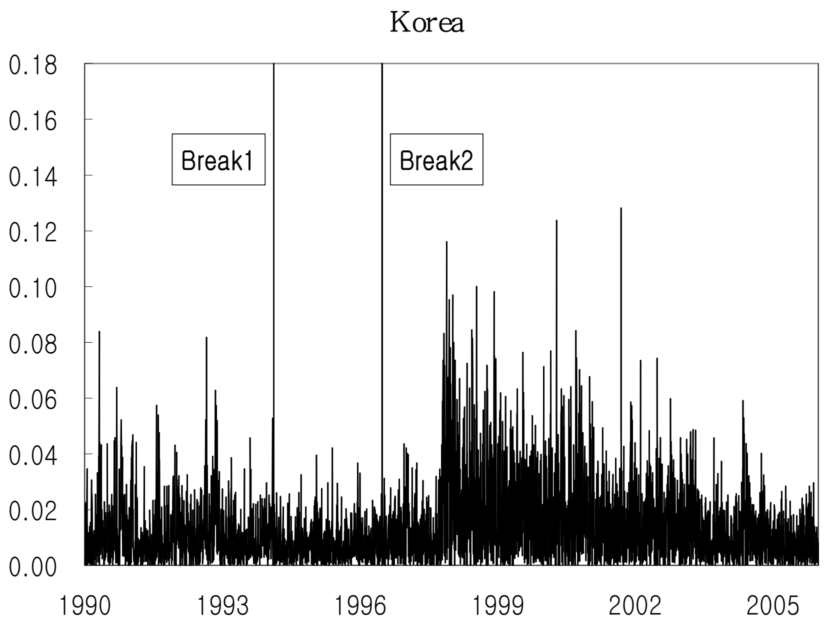
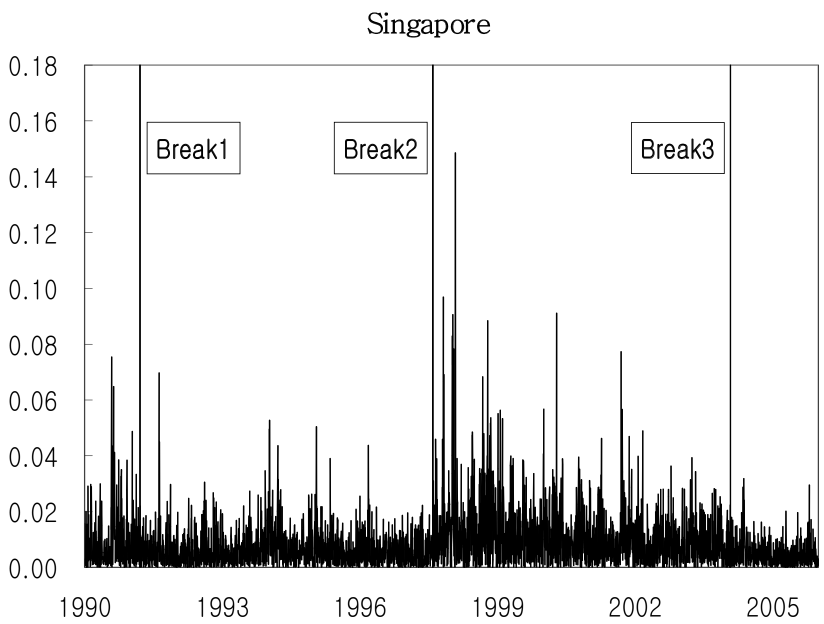


Figure 1. Continued





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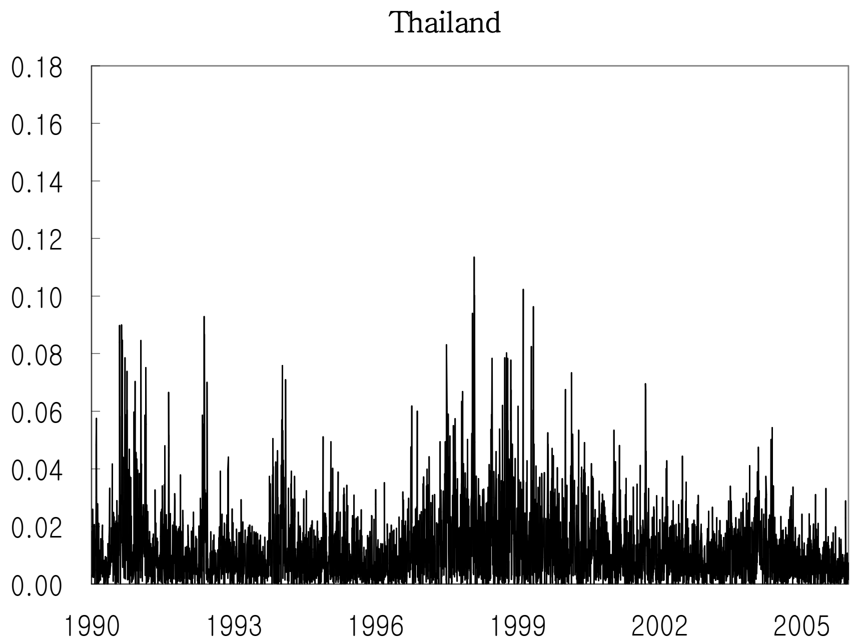


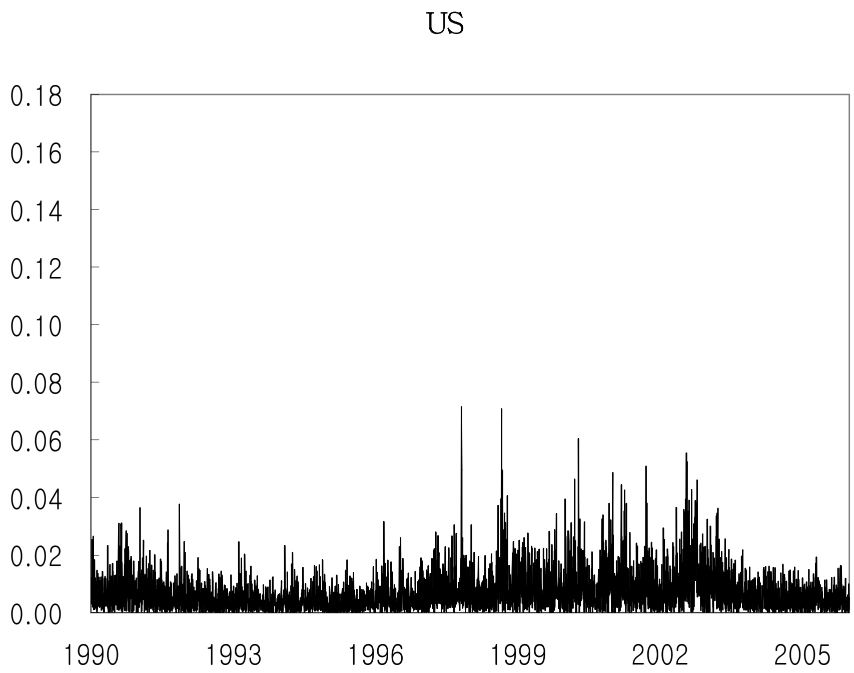
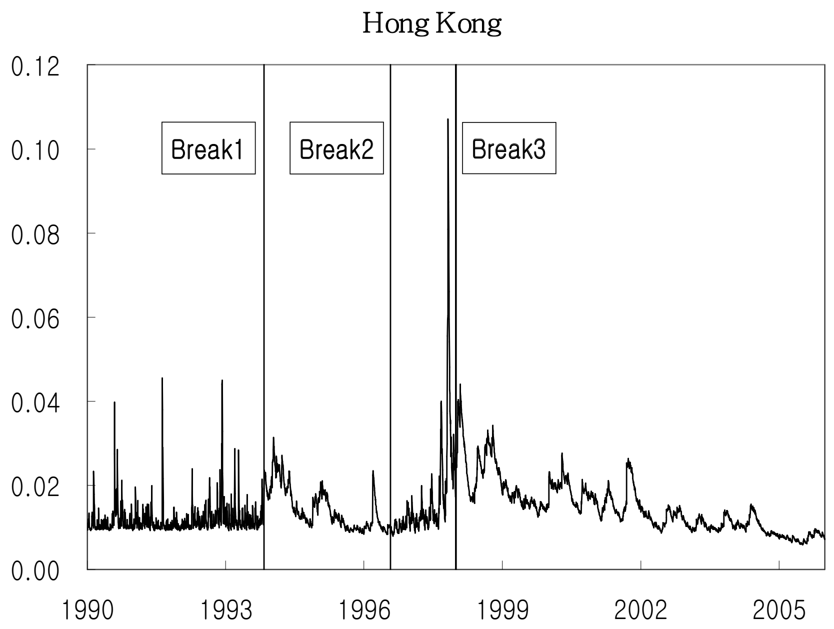


Figure 2. Graphs of GARCH volatility by market (with structural change in volatility)



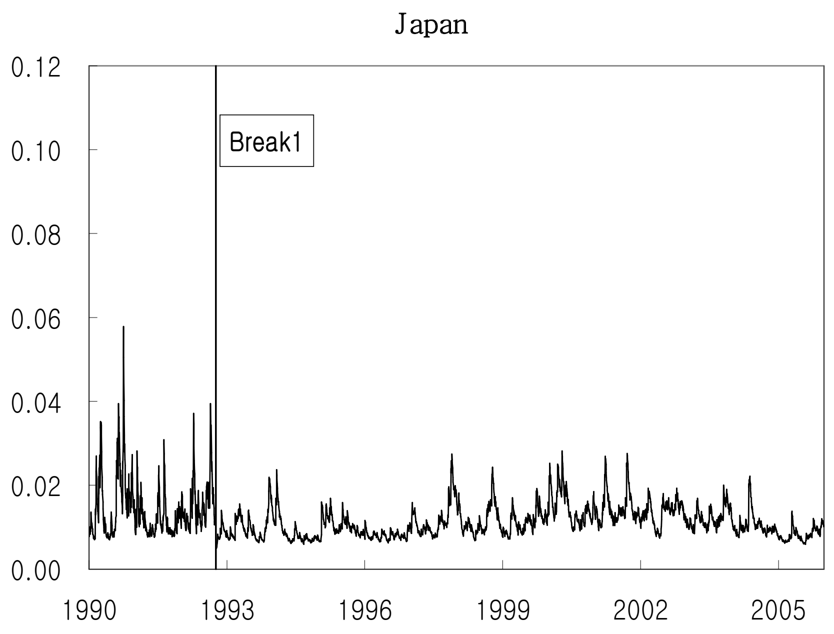
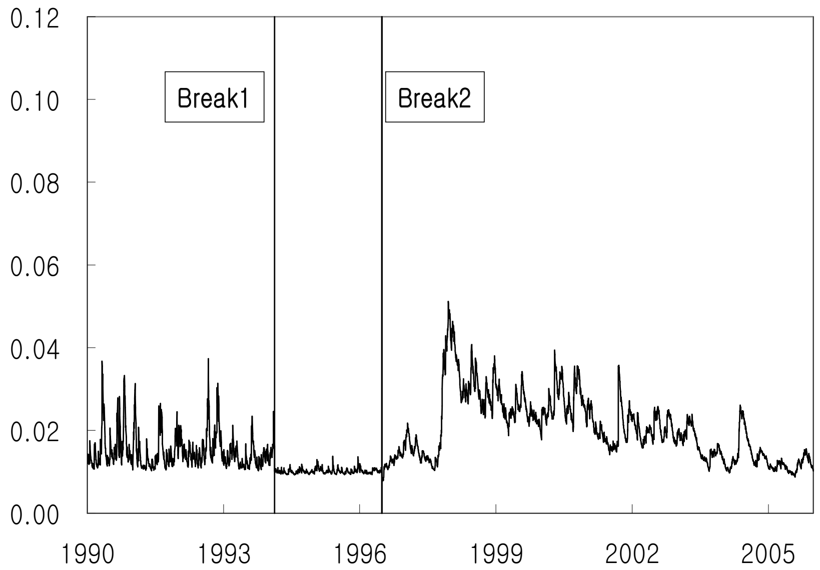


Figure 2. Continued
(with structural change in volatility)

Korea



Singapore

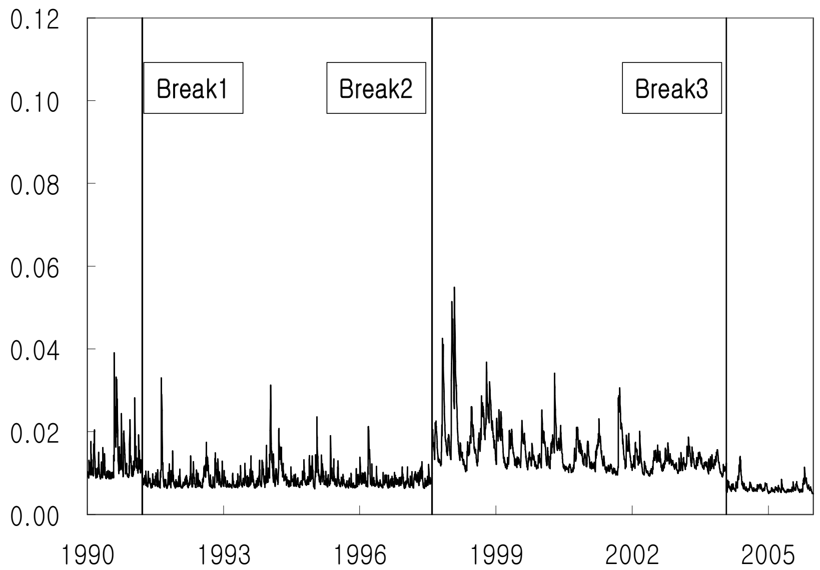


Figure 2. Continued