# Structural Breaks and Long Memory: Forecasting the Volatility of Asian Stock Markets

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This study examines the impact of structural breaks on volatility persistence, or the long memory property, in six Asian stock markets: Hong Kong, Korea, Indonesia, Malaysia, Thailand, and Singapore. We examine sudden changes associated with global financial and political events, specifically, the 1997 Asian currency crisis, the 1998 Russia crisis, the IT dot com bubbles of 2000, the 9/11 terror attack of 2001, and the recent financial crisis of 2007-2010 (sub-prime mortgage crisis and Lehman Brothers bankruptcy). When these sudden changes are incorporated into GARCH and FIGARCH models, the evidence of persistence or the long memory property vanishes from volatility. This result suggests that ignoring the effect of sudden changes overestimates volatility persistence. In addition, out-of-sample analysis confirms that volatility models, which incorporate sudden changes, provide more accurate one-step-ahead volatility forecasts than their counterparts without sudden changes. Thus, incorporating information on sudden changes in conditional variance may improve the accuracy of estimating volatility dynamics and forecasting future volatility for researchers and investors.

Key words: Volatility Forecasting, Structural Breaks, Long Memory, ICSS Algorithm

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# I. Introduction

The volatility of financial time series is affected by infrequent market structural breaks, corresponding to economic turmoil. Examples include the 1997 Asian currency crisis, the IT dot com bubbles, and the recent global crisis in 2007-2010. Empirical studies have found that such market shocks to volatility generate multiple breaks or sudden changes, which exhibit high persistence in time-varying conditional variance (Bollerslev, Chou, and Kroner, 1992; Bollerslev and Engle, 1993; Hillebrand, 2005; Baillie and Morana, 2009). This persistence feature in variance has important implications for understanding the pricing of financial assets, implementing hedging strategies, and assessing regulatory proposals to restrict international capital flows.

However, Lastrapes (1989), and Lamoureux and Lastrapes (1990), argued that ignoring such sudden changes would induce persistence in the volatility of stock returns. Thus, the inclusion of sudden changes has been known to dramatically reduce estimates of persistence in GARCH class models. Hamilton and Susmel (1994) introduced a Markov-switching ARCH model to account for structural/regime changes and, thus, structural breaks were determined by the data. This model allows for transition probabilities that change with restrictive assumption.

Subsequently, Inclán and Tiao (1994) introduced an iterated cumulative sum of squares (ICSS) algorithm to detect variance changes. The ICSS technique indentified the shifts by properly recognizing outliers, which makes it a useful tool for retrospective detection of break points in variances. Aggarwal, Inclan, and Leal (1999) investigated the large sudden shifts in the volatility of 10 emerging markets in Asia and Latin

America. They detected time points of sudden shifts using the ICSS algorithm and directly incorporated the impact of structural breaks on volatility persistence by including sudden shifts dummies into the GARCH model. They concluded that a GARCH model with “sudden change” dummies decreases the estimated persistence of volatility.

More recently, Malik and Hassan (2004) detected the time points of volatility shifts for five Dow Jones sector indexes: financial, industrial, consumer, health, and technology. They found that most breaks were associated with global economic and political events, rather than sector-specific events, and that these breaks increased volatility in most sector series. Malik, Ewing, and Payne (2005) suggested that controlling regime shifts dramatically reduces volatility persistence in the Canadian stock market. Hammoudeh and Li (2008) examined the significant reductions in volatility persistence for Gulf Cooperation Council (GCC) stock markets. Wang and Moore (2009) investigated the impact of sudden changes on volatility persistence in the transition economies of new European Union (EU) members. These studies unanimously agree that incorporating sudden changes into a GARCH model reduces volatility persistence in stock returns.

In the domestic case, Kang, Cho, and Yoon (2009) found that controlling sudden changes effectively reduces the long memory property in the Korean and Japanese stock markets using a fractionally integrated GARCH (FIGARCH) model. Kang and Yoon (2010) detected multiple sudden changes in the volatility of the KOSPI 200 sector index. They identified that sudden change is generally associated with major economic and political events. Both studies suggest that incorporating information regarding sudden changes in variance improves the accuracy of estimating volatility dynamics.

This study attempts to identify sudden changes in volatility and determines the 'true' impact of a shock on the persistence in volatility of six Asian stock markets. The primary aims of this study are threefold: First, the study utilizes recent data in order to detect multiple sudden change points. Emerging Asian markets are characterized by high volatility, and its persistence, due to global economic and political events, such as the 1997 Asian currency crisis, the 1998 Russia crisis, the IT dot com bubbles of 2000, the 9/11 terror attack of 2001, and the recent financial crisis of 2007-2010.

Second, this study also evaluates the impact of sudden changes on volatility persistence or long memory property by using GARCH and FIGARCH models. The GARCH model is conducted by incorporating this information to measure the effect of shocks on volatility persistence. Prior studies argued that sudden changes or structural breaks might give rise to spurious long memory in variance (Diebold and Inoue, 2001; Granger and Hyung, 2004; Banerjee and Urga, 2005). This study suggests that the FIGARCH model, with sudden changes, can simultaneously assess the effect of the long memory property, and structural breaks, inherent to stock markets.

Third, this study compares the out-of-sample performance of the above-stated volatility models in measuring one-step-ahead forecasting ability. Practically speaking, the GARCH and FIGARCH models with sudden changes produce better performance of forecasting ability with regard to volatility. Thus, this study argues that incorporating information on sudden changes in conditional variance can improve the accuracy of future volatility forecasting for researchers and investors.

This paper is organised as follows: Section 2 presents the methodologies for the ICSS algorithm and GARCH models. Section 3 describes the characteristics of sample

data. Section 4 provides the estimation results of the ICSS algorithm and the GARCH models. The final section provides concluding remarks.

# II. Methodology

In accordance with the work of Inclán and Tiao (1994), this study identifies sudden changes in volatility with the ICSS algorithm, and then estimates the GARCH$(1,1)$ and FIGARCH models with and without sudden change dummies.

## 1. Detecting points of sudden change in volatility

The ICSS algorithm is utilized to identify discrete sub–periods of changing volatility in stock returns. It assumes that the conditional variance of a time series is stationary over an initial period of time, until a sudden change occurs as the result of a sequence of financial events; the variance then reverts to stationary, until another market shock occurs. This process is repeated over time, generating a time series of observations with an unknown number of changes in the variance.

Where $\{\varepsilon_t\}$ denotes an independent time series with zero mean and unconditional variance $\sigma_t^2$, the variance in each interval is given by $\sigma_j^2$, $j = 0,1,\cdots,N_T$, where $N_T$ is the total number of variance changes in $T$ observations, and $1 < K_1 < K_2 < \cdots < K_{N_T} < T$ is the set of change points. The variance over $N_T$ intervals is then defined as follows:

$$\sigma_t^2 = \begin{cases} \sigma_0^2, & 1 < t < K_1 \\ \sigma_1^2, & K_1 < t < K_2 \\ \vdots & \\ \sigma_{N_T}^2, & K_{N_T} < t < T \end{cases} . \tag{1}$$

A cumulative sum of squares is utilized to determine the number of changes in variance and the point in time at which each variance shift occurs. The cumulative sum of squares from the first observation to the $k$ th point in time is expressed as follows:

$$C_k = \sum_{t=1}^{k} \varepsilon_t^2 , \qquad \text{where } k = 1, \ldots, T . \tag{2}$$

The statistic $D_k$ is defined as follows:

$$D_k = \left( \frac{C_k}{C_T} \right) - \frac{k}{T}, \qquad \text{where } D_0 = D_T = 0 , \tag{3}$$

where $C_T$ is the sum of the squared residuals from the whole sample period. Note that if there is no change in variance, the $D_k$ statistic will oscillate around zero (i.e., if $D_k$ is plotted against $k$, it will resemble a horizontal line). However, if there are one or more changes in variance, the statistical values will drift up, or down, from zero. In this context, significant changes in variance are detected using the critical values obtained from the distribution of $D_k$ under the null hypothesis of constant variance. If the maximum absolute value of $D_k$ is greater than the critical value, the null hypothesis of homogeneity can be rejected. If we define $k^*$ to be the value at which $\max_k |D_k|$ is reached, and if $\max_k \sqrt{(T/2)} |D_k|$ exceeds the critical value, $k^*$ is used as the time

point at which a variance change in the series occurs. The term $\sqrt{(T/2)}$ is required for the standardization of the distribution.

In accordance with the study of Inclán and Tiao (1994), the critical value of 1.358 is the 95th percentile of the asymptotic distribution of $\max_k \sqrt{(T/2)}|D_k|$.[1] Therefore, upper and lower boundaries can be established at $\pm 1.358$ in the $D_k$ plot. A change point in variance is identified if it exceeds these boundaries. However, if the series have multiple change points, the $D_k$ function alone is not sufficiently powerful to detect the change points at different intervals. To address this issue, Inclán and Tiao (1994) modified an algorithm that employs the $D_k$ function to systematically search for change points at different points in a series. The algorithm works by evaluating the $D_k$ function over different time periods, and those different periods are determined by the breakpoints identified by the $D_k$ plot.

## 2. Fractional integrated GARCH (FIGARCH) model

Following the example of Engle (1982), consider the time series $y_t$ and the associated prediction error $\varepsilon_t = y_t - E_{t-1}[y_t]$, in which $E_{t-1}[\cdot]$ is the expectation of the conditional mean on the information set at time $t-1$. The standard GARCH$(p,q)$ model of Bollerslev (1986) is as follows:

[1] See Table 1 illustrated in the study of Inclán and Tiao (1994).

$$\varepsilon_t = z_t \sqrt{h_t}\,, \;\; z_t \sim N(0,1)\,, \tag{4}$$

$$h_t = \omega + \alpha(L)\varepsilon_t^2 + \beta(L)\sigma_t^2\,, \tag{5}$$

where $\omega > 0$, $\alpha \geq 0$, $\beta \geq 0$, $L$ denotes the lag or backshift operator, $\alpha(L) \equiv \alpha_1 L + \alpha_2 L^2 + \cdots + \alpha_q L^q$, and $\beta(L) \equiv \beta_1 L + \beta_2 L^2 + \cdots + \beta_p L^p$. In Equation (5), the persistence of conditional variances is measured by the sum $(\alpha + \beta)$. A common empirical finding is that the sum $(\alpha + \beta)$ is close to one thereby implying that shocks are infinitely persistent, which corresponds to Engle and Bollerslev's (1986) integrated GARCH (IGARCH).

The IGARCH model captures $I(1)$ type processes for the conditional variance in the sense that an infinite persistence remains important for forecasts of all horizons. This contrasts with the GARCH model, which describes stable $I(0)$ type processes (Bollerslev and Engle, 1993). Assuming that $\nu_t = \varepsilon_t^2 - h_t$, the above GARCH $(p,q)$ model can be re-written in the form of a stationary ARMA $(p,q)$ model in the following manner:

$$\varphi(L)(1-L)\varepsilon_t^2 = \omega + \left[1 - \beta(L)\right]\nu_t\,, \tag{6}$$

where, $\varphi(L) = \left[1 - \alpha(L) - \beta(L)\right](1-L)^{-1}$ and all the roots of $\varphi(L)$ and $\left[1 - \beta(L)\right]$ lie outside the unit root circle. It is well known that financial asset returns often exhibit the long memory property in their volatility.[2] To incorporate this characteristic, the

[2] The definition of long memory is generally expressed either in the time domain or in the frequency domain. In the time domain, the long memory property is characterized by slow decay of the autocorrelation function of time series with larger sample data. This approach represents a fractional integrated process or ARFIMA. In the frequency domain, if the spectral density is unbounded at low

FIGARCH model of Baillie, Bollerslev, and Mikkelsen (1996) can be obtained by replacing the difference operator $(1-L)$ in Equation (6) with a fractional differencing operator $(1-L)^d$ as follows:

$$\phi(L)(1-L)^d \varepsilon_t^2 = \omega + [1-\beta(L)]v_t . \tag{7}$$

A FIGARCH $(1,d,1)$ model can thus be specified as:

$$h_t = \omega(1-\beta)^{-1} + \left[1-(1-\beta L)^{-1}(1-\alpha L)^{-1}(1-L)^d\right] \varepsilon_t^2 , \tag{8}$$

where $0 \le d \le 1$ is the fractional difference parameter. The FIGARCH $(1,d,1)$ model provides greater flexibility for modeling the conditional variance because it accommodates the covariance stationary GARCH model when $d=0$, and the IGARCH model when $d=1$, in special cases. For the FIGARCH model, the persistence of shocks to either the conditional variance or the degree of long memory is measured by the fractional differencing parameter $d$. Thus, the attraction of the FIGARCH model is that, for $0<d<1$, it is sufficiently flexible to allow for an intermediate range of persistence (Baillie, Bollerslev, and Mikkelsen, 1996). The FIGARCH model can be estimated by an approximate quasi-maximum likelihood estimation technique (Bollerslev and Wooldridge, 1992).

frequencies, the time series has a long memory process. Both definitions are not equivalent but connected by the Hurst exponent, or Hurst coefficient.

### 3. GARCH and FIGARCH models with multiple sudden changes

Recent empirical studies have argued that the GARCH and FIGARCH models tend to overestimate volatility persistence when sudden changes or regime shifts in conditional variance are prevalent and ignored. In an effort to calculate accurate estimates of the model parameters, sudden changes should be incorporated into the standard GARCH and FIGARCH models. Following the study of Aggarwal, Inclan, and Leal (1999), we modify above GARCH $(1,1)$ and FIGARCH $(1,d,1)$ models with multiple sudden changes, identified via the ICSS algorithms, as follows:

$$h_t = \omega + d_1 D_1 + \cdots + d_n D_n + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1}, \tag{9}$$

$$h_t = \omega(1-\beta)^{-1} + [1-(1-\beta L)^{-1}(1-\alpha L)^{-1}(1-L)^d]\ \varepsilon_t^2 + d_1 D_1 + \cdots + d_n D_n\ , \tag{10}$$

where $D_1,\ldots,D_n$ are dummy variables that take a value of one from each point of sudden change of variance onwards, and take a value of zero elsewhere.

## III. Data and the descriptive statistics

This study considers the representative stock indices of six Asian stock markets: Hang Seng (Hong Kong), KOSPI (Korea), JKSE (Indonesia), KLCI (Malaysia), SET (Thailand) and STI (Singapore). All of these index series consist of weekly price

observations, and cover the sample period from 4 January 1992, to 17 December 2011.[3] The sample period was limited by the availability of data on emerging Asian stock markets. Still, this sample period includes major events such as the 1997 Asian currency crisis, the 1998 Russian crisis, the 2000 IT dot com bubbles, the 9/11 terror attack in 2001, and the recent global financial crisis (sub-prime mortgage crisis, and Lehman Brothers bankruptcy) in the period from 2007 to 2010.

**<Table 1> Descriptive Statistics and Unit Root Tests**

| | Hang Seng | KOSPI | JKSE | KLSE | SET | STI |
|---|---|---|---|---|---|---|
| Panel A: Descriptive statistics | | | | | | |
| Mean | 0.138 | 0.104 | 0.263 | 0.093 | 0.036 | 0.076 |
| S.D. | 3.616 | 4.139 | 3.850 | 3.045 | 3.843 | 3.199 |
| Max. | 13.92 | 17.43 | 18.80 | 24.58 | 21.84 | 18.48 |
| Min. | -19.92 | -22.92 | -23.30 | -19.03 | -26.66 | -24.21 |
| Skew. | -0.379 | -0.432 | -0.417 | 0.042 | -0.232 | -0.762 |
| Kurt. | 5.615 | 6.935 | 7.755 | 11.76 | 7.298 | 13.19 |
| J-B | 321.97*** | 704.21*** | 1005*** | 3332*** | 811.49*** | 4609*** |
| $Q_s(12)$ | 151.68*** | 330.06*** | 310.29*** | 407.97*** | 124.18*** | 112.87*** |
| $Q_s(24)$ | 212.42*** | 414.49*** | 437.68*** | 585.63*** | 185.81*** | 249.60*** |
| Panel B: Unit root tests | | | | | | |
| ADF | -31.75*** | -34.52*** | -11.19*** | -30.74*** | -19.43*** | -33.68*** |
| PP | -31.81*** | -34.48*** | -33.46*** | -31.52*** | -31.12*** | -33.81*** |
| KPSS | 0.125 | 0.061 | 0.092 | 0.057 | 0.149 | 0.042 |

Notes: The Jarque-Bera (J-B) corresponds to the test statistic for the null hypothesis of normality in the sample return distribution. The Ljung-Box test statistic, $Q_s(n)$, checks for the serial correlation of the squared return residuals for up to the n$^{th}$ order. MacKinnon's (1991) 1% critical value is -3.435 for ADF and PP tests. The critical value for the KPSS test is 0.739 at the 1% significance level. *** indicates a rejection of the null hypothesis at the 1% significance level.

[3] All sample index data are obtained from the database of Newinfomax.

The weekly price series were converted into the nominal logarithmic percentage return series for all sample indices, i.e., $y_t = 100 \times \ln\left(P_t / P_{t-1}\right)$ for $t = 1, 2, \ldots, T$, where $y_t$ is the returns of each index at time $t$, $P_t$ is the current index, and $P_{t-1}$ is the index of the previous week.[1]

Table 1 shows the descriptive statistics and results of the unit root test for all six Asian stock returns. As shown in Panel A of Table 1, the means of all sample return series are rather small, and the corresponding standard deviations (S.D.) of returns are substantially higher. Based on the values of skewness (Skew.), excess kurtosis (Kurt.), and the Jarque-Bera (J-B) statistics, we can determine that all of the return series follow a leptokurtic distribution, which has a higher peak and fatter tail than a normal distribution. The Ljung-Box Q statistics, $Q_s(n)$, for the squared return series are extremely high, indicating the rejection of the null hypothesis of no serial correlation.

Additionally, Panel B of Table 1 provides the results of three types of unit root test: the augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and Kwiatkowski, Phillips, Schmidt, and Shin (KPSS). The null hypothesis of ADF, and PP tests is that a time series contains a unit root, whereas the KPSS test has the null hypothesis of a stationary process. As shown in Table 1, large negative values for ADF, and PP test statistics reject the null hypothesis of a unit root, whereas the KPSS test statistic does not reject the null hypothesis of stationarity, with a significance level of 1%. Thus, as the results indicate, all return series are a stationary process.

[1] Weekly returns are used in order to avoid the problem of non-synchronous trading and day-of-week effects (Ramchand and Susmel, 1998; Ng, 2000; Skintzi and Refenes, 2006).

# IV. Empirical results

## 1. Sudden changes in volatility

The ICSS algorithm calculates standard deviations between change points to determine the number of sudden changes. Figure 1 illustrates the returns for six Asian stock return series, with the points of sudden change and ±3 standard deviations. Table 2 indicates the time periods of sudden changes in volatility as identified by the ICSS algorithm.

Looking at Figure 1 and Table 2, all series returns had similar time points of sudden changes in volatility, which correlated with global economic events.[2] With respect to the Hang Seng index, the first significant increase in volatility occurred right after the start of the 1997 Asian currency crisis, and the 1998 Russia crisis. This increase in volatility continued up to the end of 2001 due to the dot com bubbles and the 9/11 terror attack. IT stock company values soared due to speculative trading, but the bubble collapsed on May 10, 2000. The 9/11 terror attack led to a postponement in the recovery of the global economy. The second volatility increase was due to the recent global financial crisis (subprime mortgage crisis) during the years from 2007 to 2010.

The KOSPI experienced increased volatility due to the 1997 Asian currency crisis, and the 1998 Russia crisis. The second volatility change was related to political and domestic events, including the IT dot com bubbles, the 9/11 terror attack, the Iraq war, and the credit card debt crisis. Domestic credit card companies experienced a liquidity

[2] Volatility decreases mean that the market returns to a tranquil period; our explanation only considers volatility increases.

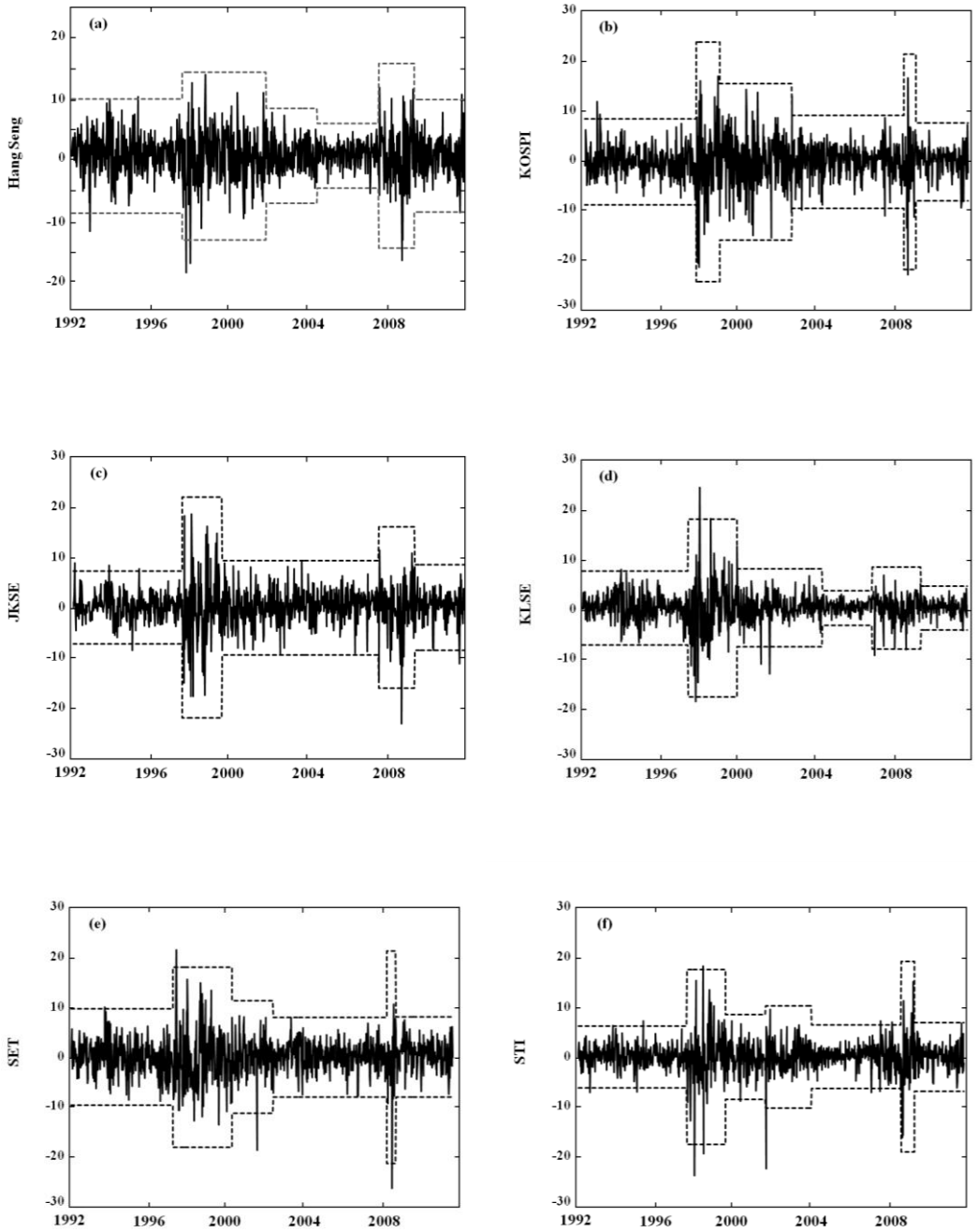
crisis at the end of November 2003. The third increase in volatility corresponded to the recent US financial crisis (the Lehman Brothers bankruptcy) in September of 2008.

The JKSE experienced two regime shifts corresponding to the 1997 Asian currency crisis, and the US sub–prime mortgage crisis of 2007–2009. The KLSE showed a volatility increase due to the Asian currency crisis, and then a volatility decrease that may simply indicate a return to a more tranquil period. In the case of both the JKSE and the KLSE, the impact to volatility of the 1997 Asian crisis was much stronger than that of the recent global financial crisis.

Like other markets, both the SET and STI sectors exhibited similar break points of volatility changes corresponding to the 1997 Asian currency crisis and the recent global financial crisis. A plot of both markets shows a short-lived sudden jump in 2008, due to the Lehman Brothers bankruptcy. Interestingly, both the SET and the STI markets are more susceptible to the impact of the recent global financial crisis than they were to the impact of the 1997 Asian crisis.

Most volatility changes in these six Asian stock markets were associated with global economic and political events rather than sector specific events. In fact, all six markets experienced a similar change due to volatility spillovers across international markets. As argued by Engle, Ito, and Lin (1990), volatility in one financial market is transmitted to other markets like ‘a meteor shower’. Thus, a single event can affect different sectors simultaneously, and cause similar volatility breaks.

**<Figure 1> Weekly Stock Returns: (a) Hang Seng, (b) KOSPI, (c) JKSE, (d) KLSE, (e) SET, (f) STI**




Note: Bands (dot lines) are at ±3 standard deviations, where the ICSS algorithm estimates structural change points.

**<Table 2> Sudden Changes in Volatility as Detected by the ICSS Algorithm**

| Series | S.D. | Time period | Events |
|---|---|---|---|
| Hang Seng | 3.2479 | 4 January 1992–<br>9 August 1997 | |
| | **4.7582** | 16 August1997–<br>10 November 2001 | Asian currency crisis; Russia crisis, dot com bubbles; 9/11 terror attack |
| | 2.6996 | 17 November 2011–<br>19 June 2004 | |
| | 1.8316 | 26 June 2004–<br>4 August 2007 | |
| | **5.2461** | 11 August 2007–<br>23 May 2009 | US sub–prime mortgage crisis; Global financial crisis |
| | 3.1943 | 23 May 2009–<br>17 December 2011 | |
| KOSPI | 2.9043 | 4 January 1992–<br>18 December 1997 | |
| | **8.1037** | 25 December 1997–<br>16 January 1999 | Asian currency crisis; Russia crisis |
| | **5.2884** | 23 January 2000–<br>12 October 2002 | Dot com bubbles; 9/11 terror attack, Credit card debt crisis |
| | 3.1308 | 19 October 2002–<br>8 August 2008 | |
| | **7.2835** | 16August 2008–<br>28 March 2009 | US sub–prime mortgage crisis; Global financial crisis |
| | 2.6545 | 4 April 2009–<br>17 December 2011 | |
| JKSE | 2.4343 | 4 January 1992–<br>26 July 1997 | |
| | **7.3835** | 2 August 1997–<br>7 August 1999 | Asian currency crisis; Russia crisis |
| | 3.1521 | 14 August 1999–<br>4 August 2007 | |
| | **5.3868** | 11 August 2007–<br>30 May 2009 | US sub–prime mortgage crisis; Global financial crisis |
| | 2.8609 | 6 June 2009–<br>17 December 2011 | |

**<Table 2> (Continued) Sudden Changes in Volatility as Detected by the ICSS Algorithm**

| Series | S.D. | Time period | Events |
|---|---|---|---|
| KLSE | 2.5002 | 4 January 1992–<br>28 June 1997 | |
| | **6.0270** | 5 July 1997–<br>8 January 2000 | Asian currency crisis; Dot com bubbles |
| | 2.6422 | 15 January 2000–<br>5 June 2004 | |
| | 1.1799 | 12 June 2004–<br>6 January 2007 | |
| | 2.7912 | 13 January 2007–<br>18 July 2009 | US sub–prime mortgage crisis; Global financial crisis |
| | 1.4873 | 25 July 2009–<br>17 December 2011 | |
| SET | 3.2713 | 4 January 1992–<br>26 April 1997 | |
| | **6.1015** | 3 May 1997<br>27 May 2000* | Asian currency crisis; Dot com bubbles |
| | 3.8218 | 3 June 2000–<br>20 July 2002 | |
| | 2.6924 | 27 July 2002–<br>28 June2008 | |
| | **7.1952** | 5 July 2008–<br>13 December 2008 | US sub–prime mortgage crisis; Global financial crisis |
| | 2.7115 | 20 December 2008–<br>17 December 2011 | |
| STI | 2.0911 | 4 January 1992–<br>9 August 1997 | |
| | **5.9422** | 16 August 1997–<br>14 August 1999 | Asian currency crisis; Russia crisis |
| | 2.8752 | 21 August 1999–<br>8 September 2001 | |
| | 3.4651 | 15 September 2001–<br>24 January 2004 | 9/11 terror attack |
| | 2.1654 | 31 January 2004–<br>13 September 2008 | |
| | **6.4729** | 20 September 2008–<br>23 May 2009 | Lehman Brothers bankruptcy; Global financial crisis |
| | 2.3335 | 30 May 2009–<br>17 December 2011 | |

Notes: Bold type indicates the largest value of standard deviation within the time period for sudden changes in volatility. * denotes period of increased volatility. Time periods detected by ICSS algorithm.

## 2. GARCH and FIGARCH estimation with and without sudden changes

Having identified sudden changes in volatility, the next step is to incorporate these sudden changes into the GARCH and FIGARCH models and examine the impact of sudden change in volatility persistence. Tables 3 and 4 present the estimation results from the GARCH$(1,1)$ and FIGARCH$(1,d,1)$ models, with and without sudden change dummy variables.

In the GARCH$(1,1)$ model of Table 3, the model without dummy variables evidences highly significant $\alpha$ and $\beta$ values, and the sums of these two parameters are close to one, reflective of volatility persistence (i.e., shocks have a permanent impact on the variance of returns).

However, the inclusion of dummy variables for sudden changes reduces the persistence of conditional variance in six stock returns. The KOSPI shows the largest decline in volatility persistence with 0.324, while the KLSE shows the smallest decline in volatility persistence with 0.119. Thus, these results are consistent with the view of Aggarwal, Inclan, and Leal (1999), Malik and Hassan (2004), Hammoudeh and Li (2008), and Wang and Moore (2009): the standard GARCH model overestimates volatility persistence when ignoring regime shifts in conditional variance.

In the FIGARCH$(1,d,1)$ model results, presented in Table 4, the model without dummy variables reveals that the fractional difference parameter $d$ differs significantly from the cases of GARCH$(d=0)$ and IGARCH$(d=1)$, implying that the volatility of both returns exhibits long memory processes.

**<Table 3> GARCH $(1,1)$ Parameters with and without Dummy Variables for Sudden Changes in Volatility**

Panel A: GARCH $(1,1)$ model without dummy variables

| Series | $\alpha$ | $\beta$ | $(\alpha+\beta)$ | $Q_s(12)$ | $Q_s(24)$ | $LM(5)$ | AIC |
|---|---|---|---|---|---|---|---|
| Hang Seng | 0.087 (0.012)*** | 0.906 (0.014)*** | 0.993 | 7.224 [0.704] | 12.56 [0.944] | 0.410 [0.842] | 5.251637 |
| KOSPI | 0.133 (0.034)*** | 0.846 (0.032)*** | 0.973 | 2.927 [0.983] | 11.13 [0.972] | 0.113 [0.989] | 5.429972 |
| JKSE | 0.132 (0.071)* | 0.818 (0.108)*** | 0.950 | 6.910 [0.734] | 12.17 [0.954] | 0.479 [0.792] | 5.297149 |
| KLSE | 0.087 (0.020)*** | 0.909 (0.019)*** | 0.996 | 5.823 [0.829] | 51.11 [0.000] | 0.640 [0.669] | 4.635877 |
| SET | 0.076 (0.042)* | 0.899 (0.052)*** | 0.975 | 7.051 [0.721] | 11.88 [0.959] | 0.121 [0.988] | 5.385549 |
| STI | 0.068 (0.026)** | 0.926 (0.028)*** | 0.994 | 8.981 [0.533] | 16.58 [0.785] | 0.113 [0.989] | 4.952778 |

Panel B: GARCH $(1,1)$ model with dummy variables

| Series | $\alpha$ | $\beta$ | $(\alpha+\beta)$ | Persistence decline | $Q_s(12)$ | $Q_s(24)$ | $LM(5)$ | AIC |
|---|---|---|---|---|---|---|---|---|
| Hang Seng | 0.049 (0.018)*** | 0.797 (0.082)*** | 0.846 | 0.147 | 12.23 [0.269] | 18.02 [0.705] | 0.403 [0.846] | 5.224267 |
| KOSPI | 0.114 (0.037)*** | 0.535 (0.444) | 0.649 | 0.324 | 9.988 [0.442] | 24.13 [0.340] | 0.430 [0.828] | 5.385382 |
| JKSE | 0.090 (0.030)*** | 0.595 (0.098)*** | 0.685 | 0.265 | 5.685 [0.841] | 10.29 [0.983] | 0.160 [0.977] | 5.230289 |
| KLSE | 0.074 (0.019)*** | 0.803 (0.056)*** | 0.877 | 0.119 | 9.608 [0.475] | 59.26 [0.000] | 0.686 [0.634] | 4.598663 |
| SET | 0.064 (0.028)** | 0.593 (0.099)*** | 0.657 | 0.318 | 8.253 [0.604] | 16.92 [0.767] | 0.663 [0.651] | 5.312801 |
| STI | 0.070 (0.027)*** | 0.795 (0.074)*** | 0.865 | 0.129 | 11.55 [0.316] | 23.13 [0.394] | 0.025 [0.999] | 4.829830 |

Notes: The Ljung–Box test statistic, $Q_S(n)$, checks the serial correlation of squared residual series. The $LM(5)$ test statistic checks the remaining ARCH effects in estimated residuals. AIC is the Akaike information criterion. P–values are in brackets and standard errors are in parentheses.

**<Table 4> FIGARCH $(1,d,1)$ Parameters with and without Dummy Variables for Sudden Changes in Volatility**

| Panel A: FIGARCH $(1,d,1)$ model without dummy variables | | | | | | | |
|---|---|---|---|---|---|---|---|
| Series | α | β | $d$ | $Q_s(12)$ | $Q_s(24)$ | $LM(5)$ | AIC |
| Hang Seng | 0.068 (0.138) | 0.902 (0.049)*** | 0.958 (0.166)*** | 7.448 [0.682] | 13.11 [0.929] | 0.471 [0.797] | 5.253145 |
| KOSPI | 0.118 (0.108) | 0.546 (0.187)*** | 0.550 (0.197)*** | 2.937 [0.983] | 12.17 [0.953] | 0.126 [0.986] | 5.430098 |
| JKSE | 0.238 (0.110)** | 0.444 (0.117)*** | 0.373 (0.146)** | 4.172 [0.939] | 10.67 [0.979] | 0.291 [0.917] | 5.290534 |
| KLSE | 0.070 (0.108) | 0.620 (0.143)*** | 0.594 (0.124 )*** | 6.509 [0.770] | 56.82 [0.000] | 0.635 [0.672] | 4.635613 |
| SET | 0.197 (0.261) | 0.416 (0.288) | 0.347 (0.145)** | 8.985 [0.533] | 13.82 [0.907] | 0.240 [0.944] | 5.385998 |
| STI | 0.383 (0.152)*** | 0.717 (0.136)*** | 0.406 (0.081)*** | 38.69 [0.000] | 55.23 [0.000] | 0.141 [0.982] | 4.927677 |
| Panel B: FIGARCH $(1,d,1)$ model with dummy variables | | | | | | | |
| Series | α | β | $d$ | $Q_s(12)$ | $Q_s(24)$ | $LM(5)$ | AIC |
| Hang Seng | 0.072 (0.206) | 0.182 (0.205) | 0.091 (0.047) | 13.91 [0.177] | 20.26 [0.566] | 0.202 [0.962] | 5.224093 |
| KOSPI | 0.515 (0.250)** | 0.422 (0.194)** | 0.024 (0.062) | 10.11 [0.430] | 23.13 [0.394] | 0.662 [0.652] | 5.386469 |
| JKSE | 0.645 (0.135)*** | 0.574 (0.113)*** | 0.021 (0.038) | 6.064 [0.809] | 11.09 [0.973] | 0.190 [0.966] | 5.231832 |
| KLSE | 0.236 (0.214) | 0.353 (0.127)*** | 0.154 (0.097) | 9.224 [0.510] | 49.83 [0.000] | 0.737 [0.595] | 4.600852 |
| SET | 0.793 (0.071)*** | 0.651 (0.060)*** | 0.099 (0.049)** | 8.462 [0.583] | 17.31 [0.745] | 0.517 [0.763] | 5.310248 |
| STI | 0.039 (0.192) | 0.008 (0.108) | 0.109 (0.085) | 12.20 [0.272] | 27.47 [01.93] | 0.153 [0.979] | 4.833539 |

Notes: The Ljung–Box test statistic, $Q_s(n)$, checks the serial correlation of squared residual series. The $LM(5)$ test statistic checks the remaining ARCH effects in estimated residuals. AIC is the Akaike information criterion. P–values are in brackets and standard errors are in parentheses.

However, after incorporating sudden changes into the FIGARCH$(1,d,1)$ model, the estimated values of parameter $d$ reduces, and becomes statistically insignificant at the 5% level, and the presence of long memory in volatility disappears, except for the SET. Thus, it appears that ignoring sudden changes in conditional variances spuriously generates the presence of long memory in volatility. As a result, the long memory property in the volatility of six Asian stock markets is often exaggerated by sudden changes corresponding to global financial events. This finding is consistent with that of Kang, Cho, and Yoon (2009), who demonstrated that controlling sudden changes effectively reduces the long memory property in the volatility of Korean and Japanese stock markets.

Finally, we evaluated the accuracy of the model specifications using several diagnostic tests, presented in Tables 3 and 4. The insignificance of LM ARCH (5) and Ljung-Box $Q_s(12)$ and $Q_s(24)$ tests shows that no ARCH effect or serial correlation can be observed in the residual series. These diagnostic tests imply the GARCH and FIGARCH models without dummy variables were well specified. Nevertheless, the GARCH model with dummy variables performed better than the one without dummy variables, as indicated by the lower values of the Akaike information criterion (AIC).

## 3. Out-of-sample forecasts

In accordance with the relevant literature (Brailsford and Faff, 1996; Brooks and Persand, 2003; Degiannakis, 2004), daily *ex post* volatility (variance) was measured by the squared returns as follows:

$$\sigma_t^2 = r_t^2 . \tag{11}$$

To measure forecasting accuracy, we calculated the mean of absolute errors ( $MAE$ ), and the mean squared errors ( $MSE$ ), as follows:

$$MAE = \frac{1}{T}\sum_{i=1}^{T}\left|\sigma_{f,t}^2 - \sigma_{a,t}^2\right|, \tag{12}$$

$$MSE = \frac{1}{T}\sum_{i=1}^{T}\left(\sigma_{f,t}^2 - \sigma_{a,t}^2\right)^2 , \tag{13}$$

where $T$ is the number of forecasting data points, and $\sigma_{f,t}^2$ denotes the volatility forecast for day $t$, whereas $\sigma_{a,t}^2$ signifies actual volatility on day $t$.

The forecast evaluation of the one-step-ahead forecast generated from the GARCH$(1,1)$ and FIGARCH$(1,d,1)$ models with and without sudden change dummies is reported in Table 5. Smaller forecasting error statistics reflect the superior forecasting ability of a given model. An overall evaluation indicates that the GARCH and FIGARCH models with sudden change dummies provide relatively good forecasts of six Asian stock markets' volatility whereas those models without dummies seem to be a poor alternative. Thus, the results of one-step-ahead forecasting analysis suggest that the volatility models with sudden changes provide excellent out-of-sample predictability.

**<Table 5> Forecast Evaluation**

| | GARCH(1,1) model | | FIGARCH(1,d,1) model | |
|---|---|---|---|---|
| | With dummies | Without dummies | With dummies | Without dummies |
| Hang Seng | | | | |
| *MAE* | 9.918 | 18.28 | 9.567 | 17.86 |
| *MSE* | 98.36 | 334.2 | 91.54 | 318.8 |
| KOSPI | | | | |
| *MAE* | 5.618 | 13.22 | 4.995 | 12.82 |
| *MSE* | 31.56 | 174.8 | 24.95 | 164.3 |
| JKSE | | | | |
| *MAE* | 6.987 | 12.19 | 6.965 | 10.82 |
| *MSE* | 48.82 | 148.6 | 48.51 | 117.0 |
| KLSE | | | | |
| *MAE* | 3.401 | 4.967 | 2.884 | 4.587 |
| *MSE* | 11.57 | 24.67 | 8.316 | 21.04 |
| SET | | | | |
| *MAE* | 8.041 | 13.25 | 8.041 | 12.12 |
| *MSE* | 64.66 | 175.4 | 64.67 | 147.0 |
| STI | | | | |
| *MAE* | 5.175 | 8.829 | 4.558 | 12.09 |
| *MSE* | 26.78 | 77.95 | 20.78 | 146.2 |

# V. Conclusions

This study examined the impact of structural breaks on the volatility persistence or long memory property in six Asian stock markets, namely, Hong Kong, Korea, Indonesia, Malaysia, Thailand and Singapore. In particular, this study identified correct dates of sudden changes in volatility through the ICSS algorithm, and examined the 'true' impact of a shock to volatility persistence using the GARCH and FIGARCH models, with and without sudden change dummies.

This empirical analysis provides three important findings regarding the impact of sudden changes on volatility. First, the identification of sudden changes in most Asian

stock markets is largely associated with global financial and political events, specifically the 1997 Asian currency crisis, the 1998 Russia crisis, the IT dot com bubbles of 2000, the 9/11 terror attack of 2001 and the recent financial crisis of 2007-2010 (the sub-prime mortgage crisis and Lehman Brothers bankruptcy).

Second, when these sudden changes are incorporated into GARCH and FIGARCH models, the evidence of persistence, or the long memory property, vanished in the volatility estimates of six Asian stock markets. This result implies that ignoring regime shifts overestimates volatility persistence. In particular, it appears that ignoring sudden changes in conditional variances spuriously generates the presence of long memory in volatility.

Third, out-of-sample analysis confirms that volatility models incorporating sudden changes provide more accurate one-step-ahead volatility forecasts than their counterparts without sudden changes. Thus, incorporating information on sudden changes in conditional variance may improve the accuracy of estimating volatility dynamics, and forecasting future volatility for researchers and investors.

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