

Full Length Research Paper

Cross market value-at-risk evaluations in emerging markets

Chin Wen Cheong^{1*}, Zaidi Isa² and Abu Hassan Shaari Mohd Nor³

¹Research Centre of Mathematical Sciences, Multimedia University, 63100 Cyberjaya, Selangor, Malaysia.

²Pusat Pemodelan dan Analisis Data (DELTA), Faculty of Science and Technology, Universiti Kebangsaan Malaysia, 46100 Bangi, Selangor, Malaysia.

³Faculty of Economics and Management, Universiti Kebangsaan Malaysia, 46100 Bangi, Selangor, Malaysia.

Accepted 22 February, 2011

This study investigated the importance of shock and volatility dynamic transmissions in cross-market hedging and market risk evaluations. A trivariate asymmetric time-varying model is used to reveal the hidden dynamics price changes and volatility correlations among the selected Southeast Asian emerging markets after the Asian financial crisis. The results indicated that the equity markets are sharing the common information (shock) that transmitted among each other. Finally, the estimated dynamic volatility correlations are employed in various cross-market value-at-risk evaluations.

Key words: Multivariate ARCH, structural change, value at risk.

INTRODUCTION

The Southeast Asian emerging markets have received great attentions from researchers and investors across the regional and global financial markets, especially during the Asian financial crisis periods. Due to their close geographical proximity and similar economic structure, it is worth to investigate their markets interdependences in term of shock and volatility. One of the prior studies of Southeast Asian emerging markets has been examined by Tai (2007) with six Asian emerging markets (including Thailand and Malaysia) volatility spillover under their liberalization periods using a dynamic integrated capital asset pricing model. Johansson (2008) on the other hand, studied the time-varying volatilities among Malaysia, China, South Korea and Thailand bond markets and indicated strong long and short relationships. In another study, Chiang et al. (2007) suggested that the contagion effect (among Malaysia, Indonesia, South Korea, Taiwan, Thailand, Singapore and Hong Kong) had taken place during the crisis and that herding behaviour dominates the post-crisis period. Francis et al. (2001) studied the Hong Kong, South Korea and Thailand during the Asian financial crisis periods of

1997 and 1998. They claimed that the reciprocal volatility transmission existed between Hong Kong and Korea, and unidirectional volatility transmission from Korea to Thailand. Angeles and Juan (2004) examined the dynamic linkages between international stock market volatility during the Asian crisis in 12 relevant stock exchanges. They reported that significant leverage effects are due, not only to negative shocks in the market area itself, but also to foreign negative shocks. Andjelic et al. (2010) quantified the individual value-at-risk (VaR) in emerging markets using historical simulation and delta normal VaR. They reported that the accuracy in VaR for developed markets did not necessarily applied to emerging markets due to their unique characteristics.

Although the aforementioned researches have investigated the volatility transmission, there are still lacks of studies carried out on the cross market hedging and market risk evaluations that have been simultaneously undertaken in Thailand, Malaysian and Indonesian markets especially after the financial crisis. Due to this, we aim to focus on the volatility spillover between the price changes and volatility among the three major economic barometers of Thailand, Malaysia and Indonesia. In terms of analysis tools, the available econometric methodologies in the volatility transmission analysis included multivariate diagonal VECM (Bollerslev et al., 1988), constant conditional correlation model

*Corresponding author. Email: wcchin@mmu.edu.my. Tel: 603-83125249. Fax: 603-83125264.

(Bollerslev, 1990), factor autoregressive conditional heteroscedasticity model (Engle et al., 1990), BEKK model (Baba et al, 1990; Engle and Kroner, 1995) and Dynamic Conditional Correlation GARCH (Engle, 2002). For the sake of simplicity in technical estimation and convey useful statistical inferences, a trivariate asymmetric diagonal BEKK model is selected due to its positive definite covariance matrix and relatively less amount of estimated parameters among the aforementioned models. The outcomes of the multivariate time-varying volatility estimations are used to quantify the market risk called the VaR. The VaR normally defined as the worst loss for a given confidence level (for instance 95%) means one is 95% certain that at the end of a chosen risk horizon (for example, monthly), there will be no greater loss than just the VaR under normal market conditions. In portfolio analysis (Jorion, 2000), the VaR often acted as a tool to alert investors for their possible exposure risks under a particular portfolio. Most importantly, the VaR can be used as a regulation tool to avoid the self-regulated financial institutes to go bust where some institutes take on extremely high levels of risk (hope for high rewards) which may have fantastic current profit records, however, facing financial crisis or even going bankrupt in the next day. Besides the market risks, the empirical studies also show how the time-varying volatility transmission can be used to determine the dynamic hedge ratios and risk minimizing portfolio allocation in a given portfolio investment.

Background

Three emerging markets with physical geographical connection as well as economic conditions are considered in this study. They are Thailand (TSE), Malaysian (KLSE) and Indonesian (JSE). As part of the members of Association of Southeast Asian Nation (ASEAN), Thailand, Malaysia and Indonesia have always attempted to achieve greater financial integration among the ASEAN (<http://www.aseansec.org>) members with various policy and regulation such as ASEAN Free Trade Area (AFTA), ASEAN Investment Area (AIA), ASEAN Industrial Cooperation (AICO) Scheme and ASEAN Economic Community (AEC). Most importantly, they have all encountered serious financial crisis which was initiated by a massive devaluation of Thai baht and later rapidly spread to Indonesian rupiah as well as Malaysian ringgit in the year 1997. They are among the Asian emerging markets that have output depreciation with 57, 39 and 82%, respectively, after the hit of Asian financial crisis in the year 1997. The depreciations in terms of exchange rate (per unit USD) from June 1997 to July 1998 are 40.2, 39.0 and 83.2%, respectively. All the three countries happened to indicate strong economic growth (averagely 8 to 10%) and low inflation over a decade before the crisis and enjoyed the title of 'Asian Tigers' after the

'Asian Dragons' for Taiwan, Hong Kong, Singapore and Korea in the 1960s. A comprehensive study by Yu (2001) suggested that the possible causes of this crisis may be due to sinister investment tactics by developed countries (investing and then later withdrawing), collapse of bubble economies (asset prices reach beyond the purchasing power and cause debts), short-term capital used for long-term investment (debts caused bankruptcy), the nepotism between politicians and enterprises, among others. Others (Krugman, 1994), suggested that the long-term prosperity in Asian regional countries are solely due to the growth in the total factor productivity rather than the capital investments. In another study, Krugman (1997) again commented that the fascinating Asian development before the crisis has been mainly a matter of perspiration rather than inspiration. During the crisis, Thailand and Indonesia have sought the external aid packages from the IMF with the bailouts of USD 20.9 billion (twice IMF program) and USD 43 billion (fourth IMF program), respectively. Unfortunately, the Baht and Rupiah are sinking further due to the lack of confidence among the international investors, banking crisis and speculations. Malaysia on the other hand refused to seek funding from the IMF and unilaterally implemented selective capital controls and pegged the ringgit (RM) against the USD with a ratio of RM3.8 to USD1.0.

In the early 1998, all these countries were in progress towards the economic recovery. For example in Malaysia, the Malaysian National Economic Action Council (NEAC) has implemented the fixed USD currency to stabilize the RM and protected it from currency speculation in year 1998. Other than that, efforts have been paid to improve the market infrastructure in terms of cost effectiveness, competitiveness, corporate transparency and regulation of investor protection. In October 1999, the Malaysian stock market has introduced the Listing Information Network (LINK) as an internet-based facility which providing comprehensive, accurate and timely information of public listed companies' announcements, thus, enhanced the corporate disclosure for market participants. In order to strengthen the banking operations, Danaharta and Danamodal have been established to relieve the non-performing loans (NPL) and restructure the capitalization. Other efforts are such as assisting the affected financial institutes by Corporate Restructuring Committee (CRC), improving the foreign direct investment (Tourres, 2003), stimulating export, abolishing taxes on foreign portfolio investment (10% in 2001) among others. Similar approaches are also observed in Thailand and Indonesia where focuses are given to restructure the financial sector (banking) and the corporate debt. In Thai, the Financial Restructuring Authority (FRA) and Asset Management Corporation (AMC) are established in late 1997 to oversee 58 finance companies liquidation processes. In the following year, 1998, the Corporate Debt Restructuring Advisory Committee (CDRAC) was established under the supervision of Governor of Bank of

Thailand to allow both the debtors and creditors voluntarily negotiate (Charoenseang and Manakit, 2002) their debts under a market-oriented approach. For Indonesia, the AMC has been formed under the Indonesia Bank Restructuring Agency (IBRA) to handle the NPL. Under the IMF program (Nasution, 2001), Indonesia has focused on five specific targets: monetary aggregates (net domestic credit), fiscal account (public sector borrowing), external sector (external indebtedness), social safety net and finally strengthening market infrastructure. After a decade of recovery, the economic performance for three of the countries can be viewed from the macroeconomic indicators such as gross domestic product (GDP), GDP based on purchase power parity (PPP), foreign direct investment (FDI) and inflation rate. According to Lin (2010), after the Asian financial crisis (1998 to 2002), technical efficiency for banks was decreasing in Indonesia, Thailand and Malaysia. Furthermore, after the Asian financial crisis, the “scale efficiency change” and “residual index” were important factors affecting the corporate value of banks in Eastern-Asia countries. As illustrated in the Appendix A to D, all the indicators have shown tendency of upward trend across the year 2001 to 2008 with the exceptional for the inflation rate where fluctuations are observed over the years.

The remaining part of this study proceeded as follows: First, the study determined the individual one-step ahead VaR for long financial position in each market. Second, the risk in minimizing portfolio weights was determined in order to obtain the optimal capital allocation among the markets. Third, the overall diversified VaR for portfolio were computed based on the time-varying cross correlation. Fourth, the undiversified overall VaR was also evaluated to find out the market risk under a possible catastrophic financial crisis. Finally, the time-varying cross-correlation was extended to appraise the risk-minimizing hedge ratio among the pair-wise markets.

DATA SOURCE

First, the Stock Exchange of Thailand (TSE) is the national stock exchange of Thailand which is located at the capital of Thailand, Bangkok. The TSE consisted of SET Index, SET50 Index and SET100 Index. Further details such as annual market capitalization, trading volume can be obtained from their official website: <http://www.set.or.th>. Second, the public trading shares of the Malaysian stock markets are firstly established in 1960 under the Malayan Stock Exchange (MSE). In 1990, the KLSE and SES finally split into two independent stock markets. The Kuala Lumpur Stock Exchange (KLSE) demutualized becomes an exchange holding company with the name of Bursa Malaysia Berhad in 2004 which consisted of Main Board, Second Board and MESDAQ (market capitalization of US\$189

billion). Later, in June 2006, a new index series with the FTSE Group was introduced in the Malaysian stock market. The 100 listed companies in the KLCI are constructed using the weighted average method (with the based year 1977). The details and performances of KLSE are available in <http://www.klse.com.my>. Finally, the Jakarta Stock Exchange (JSE) in Indonesia is established in Batavia (Jakarta) by the Dutch East Indies in the year 1912. JSE was privatized in the year 1992 and the scripless trading system was introduced for the first time in Indonesia’s Capital Market. The Indonesia stock exchanges are based on JSE Composite and Jakarta Islamic Index (JII) to measure the daily market activities. More information can be found in <http://www.idx.co.id/>.

In order to study the economic discovery dynamic price changes and volatilities relationships among these stock markets, a long spanning data beginning in January 2001 and ending in December 2008 was obtained from the Datastream with a total of 1826 observations in each markets. In Figure 1, the first glance of the prices levels indicated upward trend across the data sets. The trading-hour differences issue is minor since all the markets are located in the similar time zone. A preliminary structural break analysis is conducted to avoid inaccurate estimations within the selected time period. In Figure 2, the cumulative sum of recursive residuals (CUSUM) tests indicated that the return series are all stable within the 5% critical lines. When turned to CUSUM-square tests, the unconditional variances are somewhat stable in TSE and JSE. For KLSE, the plot exceeded the 5% critical value in the early 2001, however, moved back to the critical boundaries at the end. The global financial markets often consisted of great numbers of extreme values (McNiel and Frey, 2000; Sarah, 2000), thus, the presence of these extreme values are believed to cause the instability. Since there is no tendency for the KLSE CUSUM, square plot consistently moved away from the critical boundaries, and we considered all the stock markets to be are somewhat stable.

METHODOLOGY

The continuous compounded return with the natural logarithm is defined as:

$$r_t = \ln \left(\frac{P_t}{P_{t-1}} \right), \quad (1)$$

where the price P_t denoted the end of day closing price for a particular trading day. For the price changes and volatility dynamics among the stock markets, the study started with the unrestricted trivariate BEKK-GARCH (1,1) which has been widely used to conduct the possible volatility spillover among one financial market to the other market. For conditional mean equations, the specification is:

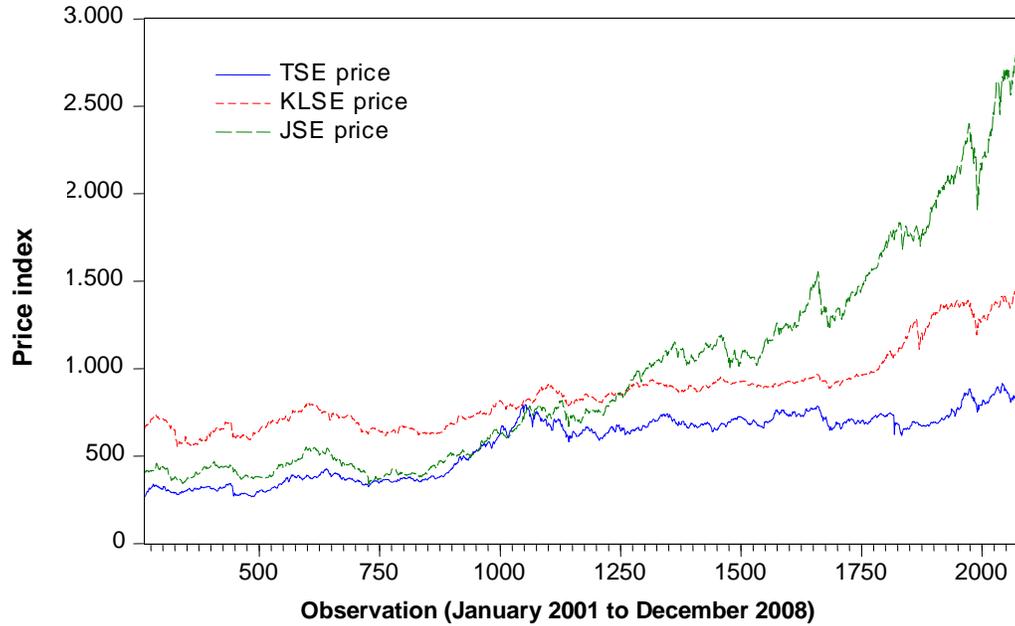


Figure 1. Price levels.

$$\begin{bmatrix} r_{1,t} \\ r_{2,t} \\ r_{3,t} \end{bmatrix} = \begin{bmatrix} \theta_{01} \\ \theta_{02} \\ \theta_{03} \end{bmatrix} + \begin{bmatrix} \theta_{11} & \theta_{12} & \theta_{13} \\ \theta_{21} & \theta_{22} & \theta_{23} \\ \theta_{31} & \theta_{32} & \theta_{33} \end{bmatrix} \begin{bmatrix} r_{1,t-1} \\ r_{2,t-1} \\ r_{3,t-1} \end{bmatrix} + \begin{bmatrix} a_{1,t} \\ a_{2,t} \\ a_{3,t} \end{bmatrix} \quad (2)$$

$$\begin{bmatrix} a_{1,t} \\ a_{2,t} \\ a_{3,t} \end{bmatrix} | \Omega_{t-1} \sim N \left(\mathbf{0}, \begin{bmatrix} \sigma_{11,t}^2 & \sigma_{12,t} & \sigma_{13,t} \\ \sigma_{21,t} & \sigma_{22,t}^2 & \sigma_{23,t} \\ \sigma_{31,t} & \sigma_{32,t} & \sigma_{33,t}^2 \end{bmatrix} \right) \quad (3)$$

with the vector representation, $r_t = \theta_0 + \theta r_{t-1} + a_t$ where θ_0 represented the long-term drifts and θ captured the impact of own past returns (diagonal elements θ_{ij}) and off-diagonal elements θ_{ij} (for $i \neq j$) quantified the return spillover. For conditional variance specification, the innovations can be written as:

or with the vector representation $a_t | \Omega_{t-1} \sim N(0, H_t)$. Under the available of past market information at $t-1$, the innovations (shocks) for each market are assumed to be normally distributed with the variance-covariance, H_t . The BEKK provided advantages in term of generality (interaction between variance-covariance) as well as less overwhelming parameters estimations issue which faced is by its compatible methodology. The positive definite covariance matrices unrestricted trivariate BEKK model specification can be expressed in the following form:

$$\begin{bmatrix} \sigma_{11,t}^2 & \sigma_{12,t} & \sigma_{13,t} \\ \sigma_{21,t} & \sigma_{22,t}^2 & \sigma_{23,t} \\ \sigma_{31,t} & \sigma_{32,t} & \sigma_{33,t}^2 \end{bmatrix} = \begin{bmatrix} \alpha_{11,0} & \alpha_{12,0} & \alpha_{13,0} \\ 0 & \alpha_{22,0} & \alpha_{23,0} \\ 0 & 0 & \alpha_{33,0} \end{bmatrix} \begin{bmatrix} \alpha_{11,0} & \alpha_{12,0} & \alpha_{13,0} \\ 0 & \alpha_{22,0} & \alpha_{23,0} \\ 0 & 0 & \alpha_{33,0} \end{bmatrix} + \text{Constant} \\ + \begin{bmatrix} \alpha_{11,1} & \alpha_{12,1} & \alpha_{13,1} \\ \alpha_{21,1} & \alpha_{22,1} & \alpha_{23,1} \\ \alpha_{31,1} & \alpha_{32,1} & \alpha_{33,1} \end{bmatrix} \begin{bmatrix} a_{1,t-1}^2 & a_{1,t-1}a_{2,t-1} & a_{1,t-1}a_{3,t-1} \\ a_{2,t-1}a_{1,t-1} & a_{2,t-1}^2 & a_{2,t-1}a_{3,t-1} \\ a_{3,t-1}a_{1,t-1} & a_{3,t-1}a_{2,t-1} & a_{3,t-1}^2 \end{bmatrix} \begin{bmatrix} \alpha_{11,1} & \alpha_{12,1} & \alpha_{13,1} \\ \alpha_{21,1} & \alpha_{22,1} & \alpha_{23,1} \\ \alpha_{31,1} & \alpha_{32,1} & \alpha_{33,1} \end{bmatrix} + \text{ARCH-term} \\ + \begin{bmatrix} \beta_{11,1} & \beta_{12,1} & \beta_{13,1} \\ \beta_{21,1} & \beta_{22,1} & \beta_{23,1} \\ \beta_{31,1} & \beta_{32,1} & \beta_{33,1} \end{bmatrix} \begin{bmatrix} \sigma_{11,t-1}^2 & \sigma_{12,t-1} & \sigma_{13,t-1} \\ \sigma_{21,t-1} & \sigma_{22,t-1}^2 & \sigma_{23,t-1} \\ \sigma_{31,t-1} & \sigma_{32,t-1} & \sigma_{33,t-1}^2 \end{bmatrix} \begin{bmatrix} \beta_{11,1} & \beta_{12,1} & \beta_{13,1} \\ \beta_{21,1} & \beta_{22,1} & \beta_{23,1} \\ \beta_{31,1} & \beta_{32,1} & \beta_{33,1} \end{bmatrix} + \text{GARCH-term} \quad (4)$$

or in the vector form:
 $H_t = A'_0 A_0 + A'_1 \varepsilon'_{t-1} \varepsilon_{t-1} A_1 + B' H_{t-1} B.$ (5)

However, this unrestricted BEKK suffered from parameter interpretation problem where an estimated parameter may affect two conditional equations simultaneously or by the sole number of

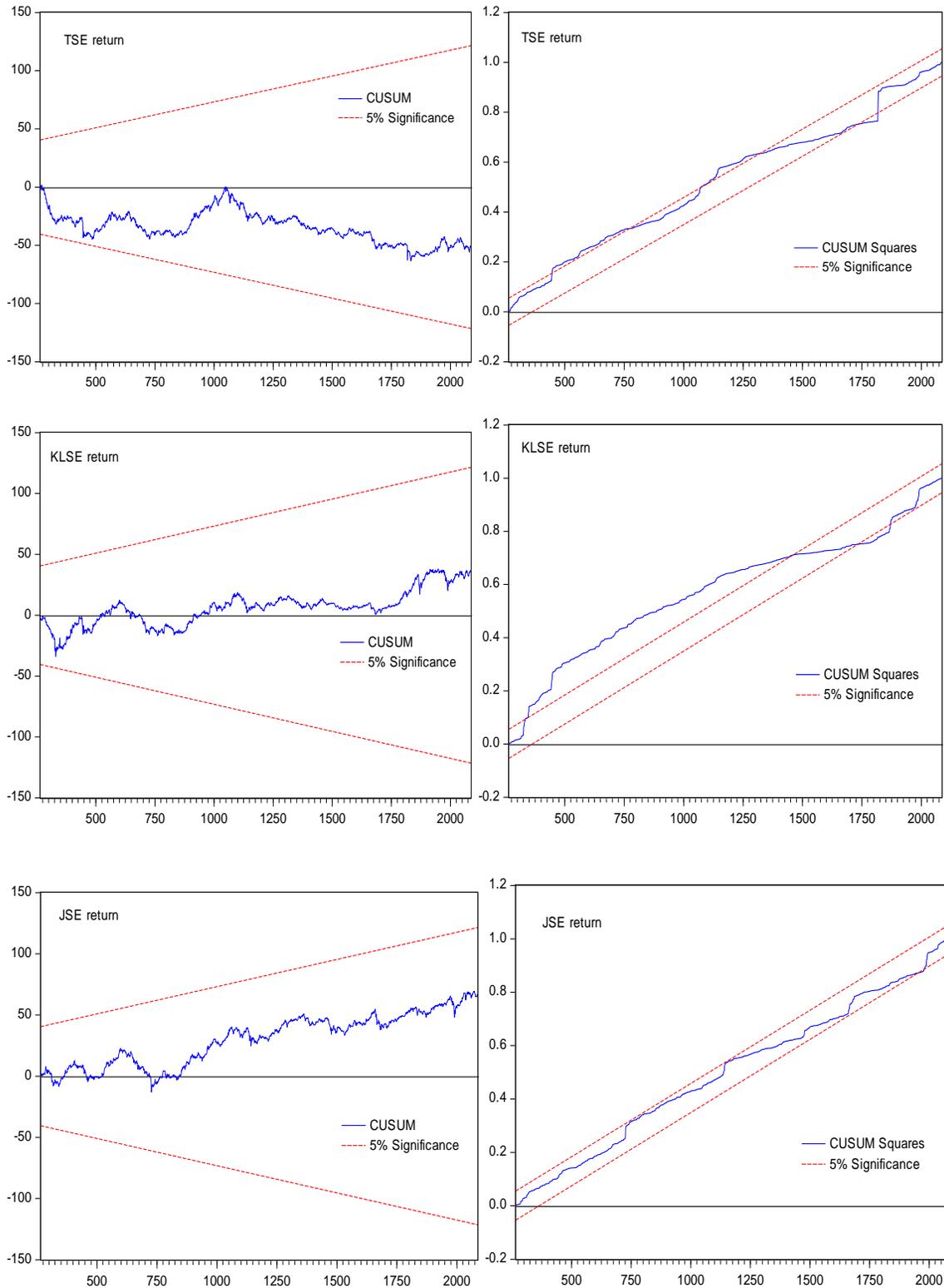


Figure 2. The CUSUM and CUSUM squares for returns series.

regressors (Baur, 2006; Tse, 2000). Thus, a restricted diagonal BEKK model with all the zero off-diagonal elements with the exceptional for the constant matrix is used in order to reduce this

severe problem. An overview for variance and covariance can be explicitly observed on how shocks and volatility are spilled over across markets and over time:

$$\sigma_{11,t}^2 = \alpha_{11,0}^2 + \alpha_{11,1}^2 a_{1,t-1}^2 + \beta_{11,1}^2 \sigma_{11,t-1}^2$$

$$\sigma_{22,t}^2 = \alpha_{12,0}^2 + \alpha_{22,0}^2 + \alpha_{22,1}^2 a_{2,t-1}^2 + \beta_{22,1}^2 \sigma_{22,t-1}^2$$

$$\sigma_{23,t} = \alpha_{12,0} \alpha_{13,0} + \alpha_{22,0} \alpha_{23,0} + (\alpha_{22,1} \alpha_{33,1}) a_{2,t-1} a_{3,t-1} + \beta_{22,1} \beta_{33,1} \sigma_{23,t-1} = \sigma_{32,t}$$

with less estimation computation while maintaining the positive definiteness of the variance-covariance matrix. Besides the clustering volatility, asymmetric news effect (Black, 1976) is also one of the important empirical stylized facts that is often observed in the worldwide financial markets. This leverage effect indicated that the downward movements (shocks) are followed by greater volatilities than upward movements of the same magnitude. In other words, changes in asset volatility tended to upsurge in response to 'bad news' and to plunge in response to 'good news'. For asymmetric diagonal BEKK model, the matrix representation for Equation 5 under the Threshold ARCH (Glaosten et al., 1993; Zakoian, 1994; Kroner and Ng, 1998) specification is:

$$H_t = A_0' A_0 + A_1' a_{t-1} a_{t-1}' A + B' H_{t-1} B + \gamma' a_{t-1} a_{t-1}' \gamma \quad (7)$$

where γ = is the diagonal matrix with elements $\gamma_{11} d_{11,t-1}$, $\gamma_{22} d_{22,t-1}$ and $\gamma_{33} d_{33,t-1}$. The additional dummy variable d denoted unity when $a_{t-1} < 0$ and zero otherwise. It is obvious that the 'bad news' contributed additional impact ($\alpha + \gamma$) to the volatility. The diagonal parameters evaluated the effects of market i ($i = 1, 2, 3$ for trivariate) to its own past negative shocks. The variance-covariance equation with the asymmetric news effect is given by:

$$\sigma_{11,t}^2 = \alpha_{11,0}^2 + \alpha_{11,1}^2 a_{1,t-1}^2 + \beta_{11,1}^2 \sigma_{11,t-1}^2 + \gamma_{11}^2 d_{11,t-1}^2 a_{1,t-1}^2$$

$$\sigma_{22,t}^2 = \alpha_{12,0}^2 + \alpha_{22,0}^2 + \alpha_{22,1}^2 a_{2,t-1}^2 + \beta_{22,1}^2 \sigma_{22,t-1}^2 + \gamma_{22}^2 d_{22,t-1}^2 a_{2,t-1}^2$$

$$\sigma_{33,t}^2 = \alpha_{13,0}^2 + \alpha_{23,0}^2 + \alpha_{33,0}^2 + \alpha_{33,1}^2 a_{3,t-1}^2 + \beta_{33,1}^2 \sigma_{33,t-1}^2 + \gamma_{33}^2 d_{33,t-1}^2 a_{3,t-1}^2$$

$$\sigma_{12,t} = \alpha_{11,0} \alpha_{12,0} + (\alpha_{11,1} \alpha_{22,1}) a_{1,t-1} a_{2,t-1} + \beta_{11,1} \beta_{22,1} \sigma_{12,t-1} + \gamma_{11} \gamma_{22} d_{11,t-1} d_{22,t-1} a_{1,t-1} a_{2,t-1}$$

$$\sigma_{13,t} = \alpha_{11,0} \alpha_{13,0} + (\alpha_{11,1} \alpha_{33,1}) a_{1,t-1} a_{3,t-1} + \beta_{11,1} \beta_{33,1} \sigma_{13,t-1} + \gamma_{11} \gamma_{33} d_{11,t-1} d_{33,t-1} a_{1,t-1} a_{3,t-1}$$

$$\sigma_{23,t} = \alpha_{12,0} \alpha_{13,0} + \alpha_{22,0} \alpha_{23,0} + (\alpha_{22,1} \alpha_{33,1}) a_{2,t-1} a_{3,t-1} + \beta_{22,1} \beta_{33,1} \sigma_{23,t-1} + \gamma_{22} \gamma_{33} d_{22,t-1} d_{33,t-1} a_{2,t-1} a_{3,t-1} \quad (8)$$

$$\sigma_{33,t}^2 = \alpha_{13,0}^2 + \alpha_{23,0}^2 + \alpha_{33,0}^2 + \alpha_{33,1}^2 a_{3,t-1}^2 + \beta_{33,1}^2 \sigma_{33,t-1}^2$$

$$\sigma_{12,t} = \alpha_{11,0} \alpha_{12,0} + (\alpha_{11,1} \alpha_{22,1}) a_{1,t-1} a_{2,t-1} + \beta_{11,1} \beta_{22,1} \sigma_{12,t-1} = \sigma_{21,t} \quad (6)$$

$$\sigma_{13,t} = \alpha_{11,0} \alpha_{13,0} + (\alpha_{11,1} \alpha_{33,1}) a_{1,t-1} a_{3,t-1} + \beta_{11,1} \beta_{33,1} \sigma_{13,t-1} = \sigma_{31,t}$$

There are some studies (Keong et al., 2010; Wang et al., 2010) that included the calendar effect to capture this additional information in the model specification. However, due to the unique characteristics for each market, this feature is not taken into account in the modelling. Under the conditional normal assumption, the gradient Marquardt method (1963) under a slight modification (correction identity matrix) from the BHHH method (Berndt et al., 1974) is considered to provide a faster convergence result in optimizing the maximum likelihood (ML) parameter estimations using the following log-likelihood function with N observations::

$$L(\Theta) = \sum_{t=1}^N l_t(\Theta) \quad (9)$$

$$l_t(\Theta) = -\ln 2\pi - \frac{1}{2} \ln |H_t(\Theta)| - \frac{1}{2} a_t'(\Theta) H_t(\Theta) a_t(\Theta) \quad (10)$$

where Θ is the vector parameter to be estimated. Consider the Newton-Raphson algorithm:

$$gradient(L_T) \approx gradient(L_T^{(0)}) + Hessian(L_T)(\eta - \eta^{(0)}) \quad (11)$$

where $L^{(0)}$ is the log likelihood function with initial vector parameter.

Under the first order condition, $\frac{\partial L_T}{\partial \eta} \Big|_{\max} \approx \frac{\partial L_T}{\partial \eta^{(0)}} + (\eta - \eta^{(0)}) \frac{\partial^2 L_T}{\partial \eta^{(0)} \partial \eta^{(0)}} = 0$. Rearranging the equation, the $(k+1)^{th}$ vector set of parameters values is defined as:

$$\eta^{(k+1)} = \eta^{(k)} - \left(\frac{\partial^2 L_T^{(k)}}{\partial \eta \partial \eta'} \right)^{-1} \frac{\partial L_T^{(k)}}{\partial \eta} \quad (12)$$

For faster and easier computation, the study has selected the BHHH (1974) method where only the outer products of the gradient vectors are computed in the iterative estimations:

$$\eta^{(k+1)} = \eta^{(k)} + \left(\sum_{t=1}^T \frac{\partial l_t^{(k)}}{\partial \eta} \frac{\partial l_t^{(k)}}{\partial \eta'} \right)^{-1} \frac{\partial L_T^{(k)}}{\partial \eta} \quad (13)$$

However, the non-normality (fat-tail property) of financial time series is often observed in the worldwide financial markets. Although, normality assumption ML estimator may fulfil the consistency condition, the departure from normality on the other hand can cause inefficient issue in the estimations. Thus, to circumvent the leptokurtosis ARCH issue, Bollerslev (1987) introduced the heavy tail standardized student-t with degree of freedom exceeding 2 in the univariate time series. Using the similar probability density function in the context of multivariate case, the student-t distribution (ν) can be written as:

$$f(\mathbf{a}_t|u, \mathbf{H}_t) = \frac{\Gamma\left[\frac{(u+k)}{2}\right]}{[\pi(u-2)]^{k/2} \Gamma\left[\frac{u}{2}\right]} \sqrt{\mathbf{H}_t} \left[1 + \frac{\mathbf{a}_t' \mathbf{H}_t \mathbf{a}_t}{(u-2)}\right]^{-(u+k)/2} \quad (14)$$

The associated log-likelihood function can be expressed as:

$$l_t(\Theta) = \ln \left\{ \frac{\Gamma\left[\frac{(u+k)}{2}\right]}{[\pi(u-2)]^{k/2} \Gamma\left[\frac{u}{2}\right]} \right\} - \frac{1}{2} \ln \mathbf{H}_t - \frac{1}{2} (u+k) \ln \left[1 + \frac{\mathbf{a}_t' \mathbf{H}_t \mathbf{a}_t}{(u-2)}\right] \quad (15)$$

For model diagnostic, the Ljung-Box Q statistic showed whether the null hypothesis of the noise terms is serially uncorrelated or random. The model selections are based on the Akaike information criterion (AIC) and Schwert information criterion (BIC) which, when evaluated from the adjusted (penalty function) average log likelihood function, are selected for the estimation evaluation.

APPLICATION IN RISK MANAGEMENT

The VaR is one of the useful risk management tools in nowadays financial and actuarial industries. The time-varying covariance provided useful information in hedging, portfolio allocation and market risk for multiple financial markets. For this particular study, the trivariate covariance matrix is restricted to two financial markets. For the probabilistic framework (Tsay, 2002) of VaR, let $\Delta R(\tau)$ be the change in value of the returns in stocks market from time t to $t+\tau$ for one of the markets. Denote the cumulative distribution function (CDF) of $\Delta r(\tau)$ by $F_\tau(x)$, the individual VaR_{*i*} (*i*=1,2) of a long position over the time horizon τ with probability α is defined as:

$$F_{long}(VaR_i) = P[\Delta r_i(\tau) \leq VaR_i] = \alpha \quad (16)$$

This definition states that the probability of a loss ($\Delta r(\tau)$) greater or equal to VaR_{*i*} over the time horizon τ is $1-\alpha$. Sometimes, one may use the quantile to estimate the VaR_{*i*}, for example, the q^{th} quantile of long position, $F_{long}(x)$ for any univariate CDF and probability α , such that $0 < \alpha < 1$ is defined as $x_p = \inf\{x | F_{long}(x) \geq \alpha\}$, where *inf* denote the smallest real number satisfying $F_{long}(x) \geq \alpha$. Under the ARCH estimation, the individual market $q\%$ quantile VaR_{*i*} can be expressed as:

$$\text{long position VaR: } VaR_i = \hat{\mu}_{i,t} + D_q \hat{\sigma}_{i,t} \quad (17)$$

where $\hat{\mu}_t, \hat{\sigma}_t$ and D are estimated conditional mean, estimated conditional standard deviation and the parametric distributions, respectively. However, the univariate ARCH results are able to determine individual market risk. In order to reveal the dynamic transmission among two or more markets, the time-varying covariances are needed to evaluate the cross-markets VaR. Let VaR_{*i*} and VaR_{*j*} be the VaR for portfolio with two long positions, the non-optimal diversified VaR based on Equation 9 can be written as:

$$VaR_{\text{diversified},ij}(\text{I}) = \sqrt{VaR_i^2 + VaR_j^2 + 2\rho_{ij} VaR_i VaR_j} \quad (18)$$

where ρ is the time-varying cross-correlation coefficient between the two index with the definition $\rho_{ij} = \frac{\sigma_{ij,t}}{\sqrt{\sigma_{ii,t} \sigma_{jj,t}}}$. When the correlation is zero, the value reduced to undiversified VaR:

$$VaR_{\text{undiversified},ij}(\text{II}) = \sqrt{VaR_i^2 + VaR_j^2} \quad (19)$$

whereas for perfect correlation of unity, the undiversified VaR becomes:

$$VaR_{\text{crisis}}(\text{III}) = VaR_i + VaR_j \quad (20)$$

This phenomenon often observed during the economic crisis where severe pressure of selling spree causes all assets and derivatives to depreciate, and consequently making it possible for the situation of perfect correlation between asset prices which occurs during the crisis. The diversified VaR provided the benefit of diversification. For optimal diversified, VaR for both markets under the Markowitz mean-variance equation, the conditional standard deviation is:

$$\sigma_{\text{portfolio}} = \sqrt{w_{ij}^2 \sigma_i^2 + (1-w_{ij})^2 \sigma_j^2 + 2w_{ij}(1-w_{ij})\rho_{ij}\sigma_i\sigma_j} \quad (21)$$

where the w is the portfolio weight for the market. In summary, there are four types of VaR that can be quantified from the pairwise markets.

Under the Kroner and Ng (1998) recommendation, the optimal portfolio holding with the zero expected returns, the risk minimizing portfolio weight can be derived as:

$$w_{ij,t} = \frac{\sigma_{jj,t} - \sigma_{ij,t}}{\sigma_{ii,t} - 2\sigma_{ij,t} + \sigma_{jj,t}} \quad (22)$$

One may interpret the portfolio weight for the first market relative to the second market at a particular time. In other words, the optimal allocation should be w_{i2} portion of the total invested capital to the first market and $(1-w_{i2})$ for the second market. It is worth noting that the weight follows the rules of:

$$w_{ij,t} = \begin{cases} 0 & w_{ij,t} < 0 \\ w_{ij,t} & 0 < w_{ij,t} < 1 \\ 1 & w_{ij,t} > 1 \end{cases} \quad (23)$$

under the mean-variance utility function. In other words, it is too risky to invest any of the capitals for negative $w_{ij,t}$ and one should

invest all the capital on the particular asset if $w_{ij,t}$ exceeded unity. Thus, the optimal diversified VaR is:

$$VaR_{\text{portfolio},ij}(\text{IV}) = (w_{ij}r_i + (1-w_{ij})r_j) + \sigma_{\text{portfolio},ij} D_q \quad (24)$$

Besides the market risk determination, the outcomes in the bivariate analysis can also be used to measure the risk-minimizing hedge ratio (Kroner and Sultan, 1993) among the two markets with the definition:

$$\beta_t = \frac{\hat{\sigma}_{ij,t}}{\hat{\sigma}_{jj,t}} \quad (25)$$

The time dependent beta β_t implies that for every unit capital long in the first market, there should be short β unit capital in the other market.

Table 1. Descriptive statistics and hypothesis tests.

Statistic	TSE	KLSE	JSE
Mean, \bar{r}	0.063489 (2.04059*)	0.042013 (2.19753*)	0.103307 (3.36364*)
Std. Dev., s	1.329512	0.816955	1.312410
Variance, s^2	1.767602 (3225.876*)	0.667415 (1218.032*)	1.72242 (3143.414*)
Skewness, $skew$	-0.843820 (-14.7206*)	-0.664808 (-11.5977*)	-0.704687 (-12.2934*)
Kurtosis, k	18.30064 (133.461*)	10.57023 (66.03191*)	8.602750 (48.87041*)
Jarque-Bera	18028.52	4494.718*	2539.445*

* Indicates 5% significance level.

EMPIRICAL RESULTS

The normality hypothesis tests are based on the statistics $\bar{r}/(s/\sqrt{T})$, $\chi^2 = (T-1)s^2$, $skew/\sqrt{6/T}$ and $(k-3)/\sqrt{24/T}$ respectively.

In Table 1, the first four moment statistics which described the central, dispersion, symmetrical property and shape (peak and tail) distribution of the return series are presented for TSE, KLSE and JSE. Overall, during the recovery period, all the financial markets indicated positive expected return. The standard deviations for TSE and JSE exceeded unity which implied that the return series are comprised with higher dispersion when compared to a normal distribution. However, contrary result is found in the KLSE return series with the standard deviation lower than unity. For symmetric analysis, all the series have shown negative skewness with the values approximately 0.7 which suggested that the series are longer left tails towards negative values. Finally, all the series are leptokurtic with the kurtosis far away from the Mesokurtic normal distribution. A series of normality based on the individual statistics are conducted and all the individual tests suggested they are deviated from the standardized normal distribution with mean zero and unity variance. In addition, the Jacque-Bera which is based on skewness and kurtosis are also conducted and all the series are found exceed the 5% critical value

$\chi^2_{(v=2)}$ which implied the rejection of null hypothesis of normal distribution. For graphical illustration, a series of quantile-quantile plots is illustrated in Figure 3 to examine whether the return series follow the specified normal and heavy-tailed distributions. In Figure 3, all the series (empirical versus normal distributions) do not lie on the straight line in their respective plots especially at the lower and upper tails. These findings implied that the return series are non-normal and slightly heavy at both the tails as compared to the normal distribution. On the other hand, the plots for return against the heavy-tailed distribution indicated better fit in a straight line which suggested that the return distributions are somewhat similar to the heavy-tailed distributions. Based on these

results, the study was motivated to use the heavy-tail assumption in the coming model specifications.

Maximum likelihood estimation

Conditional mean

$$r_{1,t} = 0.062602^* + 0.029510 r_{1,t-1} + 0.156326^* r_{2,t-2} + 0.039560^* r_{3,t-1}$$

$$r_{2,t} = 0.025023^{**} + 0.010633 r_{1,t-1} + 0.151069^* r_{2,t-2} + 0.013036 r_{3,t-1}$$

$$r_{3,t} = 0.109711^* + 0.042781^* r_{1,t-1} + 0.167988^* r_{2,t-2} + 0.108792^* r_{3,t-1}$$

* and ** indicate 5 and 10% significance levels.

Table 2 reported the estimated conditional mean equation under the trivariate BEKK specifications. The conditional mean equations enhanced the understanding of the linkages in terms of returns across the three markets. First, the long-term drifts are all statistically significant at 10% level with positive values. This finding implied that there is a tendency of upward drift in long-run during the recovery period. Second, according to the diagonal elements (θ_{ii}), only the returns of KLSE and JSE are depended on their first lag. The first-order correlation may be caused by the economic growth (Urrutia, 1995) or infrequent trading effect (Miller et al., 1993) that often occurred in the emerging market. Third, in order to investigate the cross-market return relationships, the off-diagonal parameters $\theta_{12}, \theta_{13}, \theta_{31}, \theta_{32}$ and θ_{33} are statistically significant at 5% level. In short, there cross-market impact can be summarized as follows: firstly, there are uni-directional return spillovers from KLSE to TSE and JSE and secondly, a bi-directional cross-market impact is found between TSE and JSE. These results suggested that the KLSE played an important role in news transmission into the pricing process in the TSE and JSE. On the other hand, the TSE

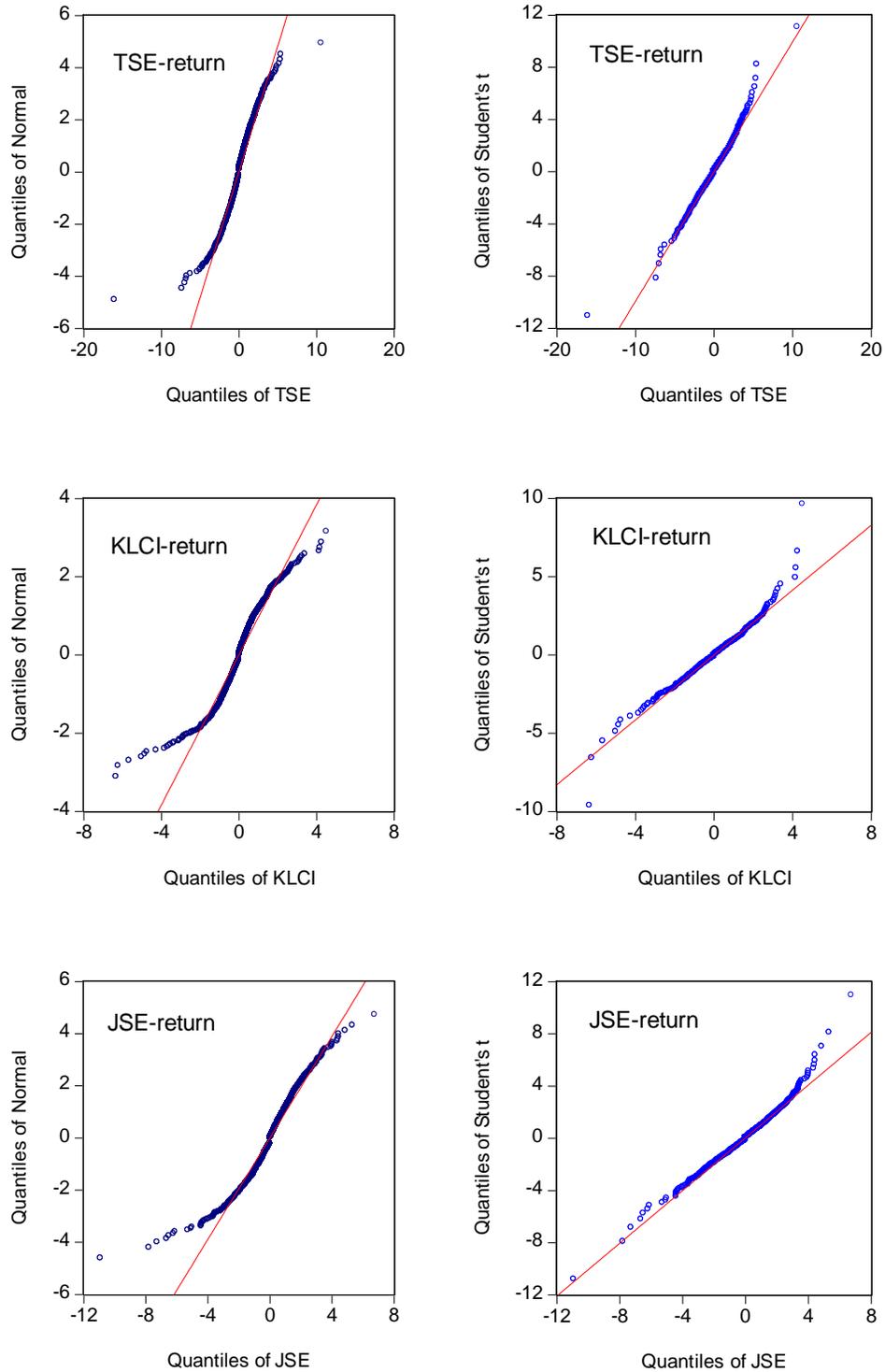


Figure 3. Q-Q plots.

and JSE mutually and closely influenced each other in their pricing processes.

Next, Table 3 showed that all the estimated results of the time-varying variance-covariance estimation supported the assumption of heavy-tailed innovation in the

model specification. This result is verified by the tail parameter (ν) which is statistically significant at 5% level with the value ranging of 6.84213. The estimated conditional variance-covariance equations are conditional variance:

Table 2. Maximum likelihood estimation for conditional return.

Conditional mean	TSE-KLCI-JSE	
	Coefficient	S.E
Constant		
θ_{01}	0.062602*	0.024786
θ_{02}	0.025023**	0.014739
θ_{03}	0.109711*	0.026191
Own first lag return		
TSE: θ_{11}	0.029510	0.023878
KLCI: θ_{22}	0.151069*	0.021892
JSE: θ_{33}	0.108792*	0.023334
Cross market first lag return		
KLCI \rightarrow TSE: θ_{12}	0.156326*	0.030733
JSE \rightarrow TSE: θ_{13}	0.039560*	0.020144
TSE \rightarrow KLCI: θ_{21}	0.010633	0.012759
JSE \rightarrow KLCI: θ_{23}	0.013036	0.011890
TSE \rightarrow JSE: θ_{31}	0.042781*	0.020887
KLCI \rightarrow JSE: θ_{32}	0.167988*	0.031549
Diagnostic		
Q(6) – TSE	9.1527	0.165
Q(6) – KLCI	7.9898	0.239
Q(6) – JSE	2.1449	0.906
Q(12) – TSE	16.339	0.176
Q(12) – KLCI	11.907	0.453
Q(12) – JSE	6.6073	0.882

* Denote the significance level at 5%; \rightarrow represents uni-directional effect; Q statistics denote the Ljung-Box serial correlation test for standardized residual.

$$\begin{aligned} \sigma_{11,t}^2 &= 0.079323 + 0.060556 a_{1,t-1}^2 + 0.048591 d_{11,t-1}^2 a_{1,t-1}^2 \\ &+ 0.865834 \sigma_{11,t-1}^2 \\ \sigma_{22,t}^2 &= 0.011205 + 0.040280 a_{2,t-1}^2 + 0.041386 d_{22,t-1}^2 a_{2,t-1}^2 \\ &+ 0.920663 \sigma_{22,t-1}^2 \\ \sigma_{33,t}^2 &= 0.214884 + 0.011684 a_{3,t-1}^2 + 0.159901 d_{33,t-1}^2 a_{3,t-1}^2 \\ &+ 0.769765 \sigma_{33,t-1}^2 \end{aligned}$$

Conditional covariance:

$$\begin{aligned} \sigma_{12,t} &= 0.004939 + 0.049388 a_{1,t-1} a_{2,t-1} + 0.892827 \sigma_{12,t-1} \\ &+ 0.044844 d_{11,t-1} d_{22,t-1} a_{1,t-1} a_{2,t-1} \end{aligned}$$

$$\begin{aligned} \sigma_{13,t} &= 0.035411 + 0.026600 a_{1,t-1} a_{3,t-1} + 0.816388 \sigma_{13,t-1} \\ &- 0.088147 d_{11,t-1} d_{33,t-1} a_{1,t-1} a_{3,t-1} \\ \sigma_{23,t} &= 0.004293 + 0.021694 a_{2,t-1} a_{3,t-1} + 0.841840 \\ &\sigma_{23,t-1} + 0.081349 d_{22,t-1} d_{33,t-1} a_{2,t-1} a_{3,t-1} \end{aligned}$$

The own ARCH and GARCH effects are captured by α_{ii} and β_{ii} , respectively and all the relevant coefficients are statistically significant at 5% level. These findings implied that the appropriateness of trivariate GARCH(1,1) processes drives the conditional variance of the three markets. For the own market, asymmetric response to negative shocks (bad news) are statistically significant at 5% level in TSE and JSE with the exceptional of KLSE.

Table 3. Maximum likelihood estimation.

Parameter	Coefficient	S.E
Constant		
α_{13}	0.079323*	0.018563
α_{12}	0.004939*	0.002369
α_{13}	0.035411*	0.009172
α_{22}	0.011205*	0.002745
α_{23}	0.004293	0.003568
α_{33}	0.214884*	0.039166
ARCH		
$\alpha_{11,1}$	0.246081*	0.029341
$\alpha_{22,1}$	0.200700*	0.024530
$\alpha_{33,1}$	0.108093*	0.045678
Asymmetric ARCH		
d_{11}	0.220434*	0.038322
d_{22}	-0.203435*	0.030900
d_{33}	0.399877*	0.038075
GARCH		
$\beta_{11,1}$	0.930502*	0.011083
$\beta_{22,1}$	0.959512*	0.005379
$\beta_{33,1}$	0.877362*	0.019658
Heavy-tailed		
ν	6.842143*	0.504941
Model selection		
L	-7598.387	
AIC	8.353107	
SIC	8.437596	
Diagnostic a_t^2		
Q(6) – TSE	0.2464	1.000
Q(6) – KLCI	34.328*	0.000
Q(6) – JSE	3.9043	0.690
Q(12) – TSE	0.5099	1.000
Q(12) – KLCI	38.140*	0.000
Q(12) – JSE	10.316	0.588

*Denote the significance level at 5%; Q statistic denote the Ljung-Box serial correlation test for standardized squared residuals.

This leverage effects implied that downward movements (shock) in the respective financial market are followed by greater volatilities than upward movements of the same magnitude. From economic view of point, this is an expected phenomenon since most of the regional financial market participants are tended to be more sensitive to bad news in the stock market. On the other hand, contrary result is indicated in the KLSE where

during the recovery period, the good news contributed higher impact to the market volatility. In conclusion, the empirical results evidenced significant volatility transmission between the three markets. Under the Ljung-Box serial correlation tests, all the series failed to reject the null hypothesis with no serial correlation (lag 6 and lag12) at 1% significant level for the standardized squared residuals, except the KLSE.

Table 4. The risk management application.

Risk	TSE	KLSE	JSE
Individual value-at-risk, VaR	2.735607	1.307368	1.994025
Pairwise value-at-risk	TSE-KLSE	TSE-JSE	KLSE-JSE
Time-varying correlation coefficient, ρ_t	0.014475	0.211262	0.008188
Risk minimizing portfolio weight, ω	0.169592	0.316582	0.724754
Diversified VaR, $VaR_{\text{diversified}}$	3.048983	3.710052	2.393332
Undiversified VaR, $VaR_{\text{undiversified}}$	3.031955	3.385215	2.384396
Optimal diversified VaR, $VaR_{\text{undiversified}}$	2.391350	3.533090	2.106900
Crisis: undiversified VaR, $VaR_{\text{diversified}}$	4.042974	4.729632	3.301393
Risk-minimizing hedge ratio, β_t	0.031627	0.285617	0.005067

Cross-market value-at-risk

Notes:

(1) the individual long position VaR, $VaR_i = \hat{\mu}_{i,t} + D_q \hat{\sigma}_{i,t}$,

where $D_q = t_{0,05, 6.842143} = 1.94318$;

(2) Time-varying correlation coefficient among the markets,

$$\rho_{ij} = \frac{\sigma_{ij,t}}{\sqrt{\sigma_{ii,t}^2 \sigma_{jj,t}^2}};$$

(3) Risk minimizing portfolio weight among two markets,

$$w_{ij,t} = \frac{\sigma_{jj,t}^2 - \sigma_{ij,t}}{\sigma_{ii,t}^2 - 2\sigma_{ij,t} + \sigma_{jj,t}^2}$$

$$\text{where } w_{ij,t} = \begin{cases} 0 & w_{ij,t} < 0 \\ w_{ij,t} & 0 < w_{ij,t} < 1 \\ 1 & w_{ij,t} > 1 \end{cases}$$

(4) Pair-wise value at risk,

$$VaR_{\text{diversified},ij}(I) = \sqrt{VaR_i^2 + VaR_j^2 + 2\rho_{ij} VaR_i VaR_j}$$

$$\text{Optimal } VaR_{\text{diversified},ij}(IV) = (w_{ij}r_i + (1 - w_{ij})r_j) + \sigma_{\text{portfolio},ij} D_q$$

(5) The risk-minimizing hedge ratio among the two markets,

$$\beta_t = \frac{\hat{\sigma}_{ij,t}}{\hat{\sigma}_{jj,t}^2}.$$

The linkages among the financial market can be further investigated in the area of risk management. Four types of value-at-risk are evaluated according to Equations 18, 19, 20 and 24. For this specific study, the portfolio investments in three markets are the relationships that can be examined by the time varying covariance σ_{ij} .

However, only the non-perfect positive correlation among the markets can benefit from the diversification feature in the portfolio investment. The overall results are presented in Table 4 where it begins with the individual VaR for each market. Suppose an investor holds a long position in TSE, KLSE and JSE with arbitrary capital, say \$C in each of the market, the VaR is forecasted using the one-step ahead forecast with 95% confidence interval from the forecast origin at $t = 1826$. Thus, the one-step ahead forecast for long position VaR are 2.735067C%, 1.307368C% and 1.994025C% in TSE, KLSE and JSE, respectively. It is found that the TSE indicated the highest risk, followed by JSE and finally, the KLSE. These findings implied that with the probability of 0.95, the potential loss encountered by the long holder of the TSE, KLSE and JSE financial position over the one day time horizon are less than or equal to 3.781377, 0.857097 and 2.046897% of the total invested capital, \$C in each market, respectively. If a portfolio consisted exclusively of \$1 million for each of the assets, the VaR in term of value will be \$37813.77, \$8570.97 and \$20468.97, respectively.

For pair-wise market risks, the combinations for the possible pair-wise markets are TSE-KLSE, TSE-JSE and KLSE-JSE. Now, for the overall pair-wise VaR, the investor (say with the overall capital \$2C) should determine the portfolio weight before making optimal portfolio allocation decisions. With multiple positions, the risk minimizing portfolio weight can be computed with the value (for example, the TSE-KLSE):

$$w_{\text{TSE-KLSE},t} = \frac{\sigma_{\text{KLSE},t}^2 - \sigma_{\text{TSE-KLSE},t}}{\sigma_{\text{TSE},t}^2 - 2\sigma_{\text{TSE-KLSE},t} + \sigma_{\text{KLSE},t}^2} = 0.169592.$$

In other words, the investor should hold \$0.169592C in the TSE over \$0.830408C in the KLSE for the optimal portfolio holding. For diversification, the dynamic cross-correlation is:

$$\rho_{TSE-KLSE,t} = \frac{\sigma_{TSE-KLSE,t}}{\sqrt{\sigma_{TSE,t}^2 \sigma_{KLSE,t}^2}} = 0.014475$$

Based on the earlier results, the four types of 5% VaR of the positions can be determined as:

$$\text{VaR}_{\text{diversified},ij}(\text{I}) = \sqrt{\text{VaR}_i^2 + \text{VaR}_j^2 + 2\rho_{ij}\text{VaR}_i\text{VaR}_j} = \$30489.83 \quad (16)$$

$$\text{VaR}_{\text{undiversified},ij}(\text{II}) = \sqrt{\text{VaR}_i^2 + \text{VaR}_j^2} = \$30319.55$$

$$\text{VaR}_{\text{crisis}}(\text{III}) = \text{VaR}_i + \text{VaR}_j = \$40429.74$$

$$\text{VaR}_{\text{portfolio},ij}(\text{IV}) = (w_{ij}r_i + (1 - w_{ij})r_j) + \sigma_{\text{portfolio},ij}D_q = \$23913.50$$

where i and j represented TSE and KLSE. From the estimated results, the optimal risk minimization VaR(IV) indicated smallest lost after considering the optimal asset allocations in the two markets. Since the cross-correlation is rather weak (0.014475), the VaR(I) and VaR(II) are almost the same with small impact by this coefficient. Finally, the VaR(III) provided the highest possible lost during the crisis with the value \$40429.74. This phenomenon is often observed during the economic crisis where severe pressure of selling spree causes all assets and derivatives to depreciate and consequently it is possible that the situation of perfectly correlation between asset prices occurs during the crisis. In other words, the panic-stricken investors who radically pull out the short-term capital are paying less attention to the diversification. Thus, the quantified market risk during the crisis is greater than normal market conditions. Table 4 shows the overall results for all the pair-wise markets and the results can be interpreted similarly with the aforementioned discussions.

For risk minimizing hedge ratio, the beta for TSE-KLSE is 0.031627 which implied that for every capital \$C in long for TSE, the investor should short \$0.031627C of the KLSE market. Since the KLSE is less risky than the TSE, almost all the capitals should invest in the long trading position in the TSE.

In conclusion, it is found that the pair-wise diversified VaR are highest between TSE-JSE, followed by TSE-KLSE and lowest in KLSE-JSE. Due to the relatively lower market risk (VaR), the minimizing risk weight suggested that it is more secured to invest in KLSE when compared to TSE and JSE. The non-optimal diversified

overall VaR indicated the risk during a possible catastrophic economic event in the stock markets. All the undiversified VaR show larger risk than the diversified VaR due to the radical selling spree without considering the portfolio diversification. Finally, the hedging ratios suggested that for every unit capital \$C that is long in the TSE, the investor should short \$0.285617C in the JSE, while in the KLSE-JSE, one should short \$0.005067C in the JSE in order to minimize the possible market risks.

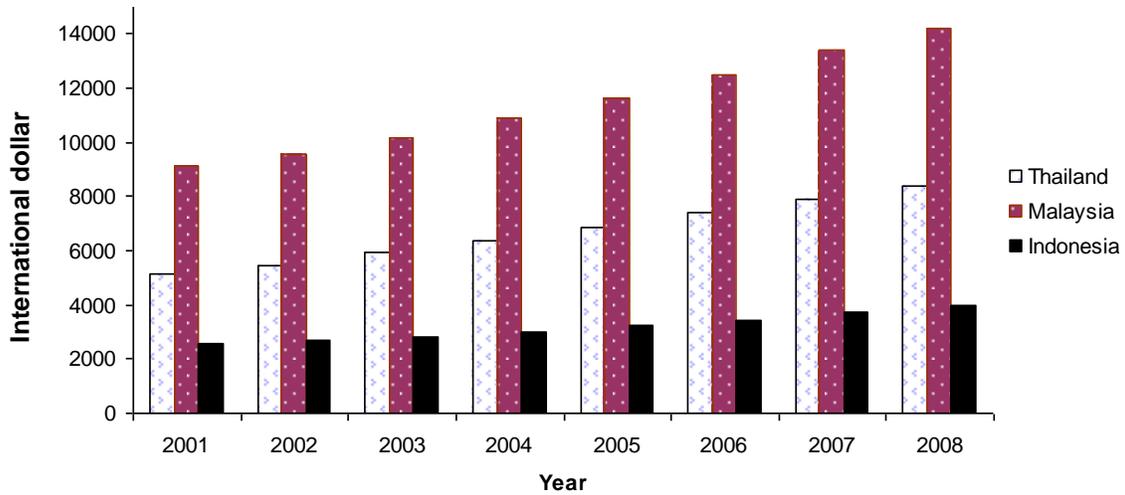
Conclusion

This study investigated the return and volatility linkages between the Southeast Asian emerging markets which included Thailand, Malaysian and Indonesian equity markets. A preliminary structural break allowed us to make accurate statistical estimation and inferences in the three markets. The hidden dynamics of interactions among the markets are evaluated by using a trivariate asymmetric BEKK model. In short, the major empirical findings that may attract the interest of investors and policy makers are three-fold: First, the trivariate return series analysis evidenced by the presence of linkages in terms of return and volatility among the markets in terms of uni- and bi-directional impact. These findings suggested that the financial markets share common information and have impact on each other according to their interrelations effects. Second, the optimal portfolio holding within the pair-wise markets is based on the risk minimizing weight which was calculated from the time varying conditional variance-covariance estimations. This information provided useful guide to quantify the optimal cross-market pair-wise value-at-risk in the forms of diversified, undiversified, crisis and optimal conditions. Third, the cross-market risk minimizing hedge ratio provided useful guide on how to hold the long and short financial positions in the pair-wise markets. It is worth noting that the stock market linkage (return and volatility) can be interpreted as the information transmission among the markets. Thus, investors and researchers should monitor all the markets closely because a shock (good or bad news) will eventually transmit across the markets through the interdependence.

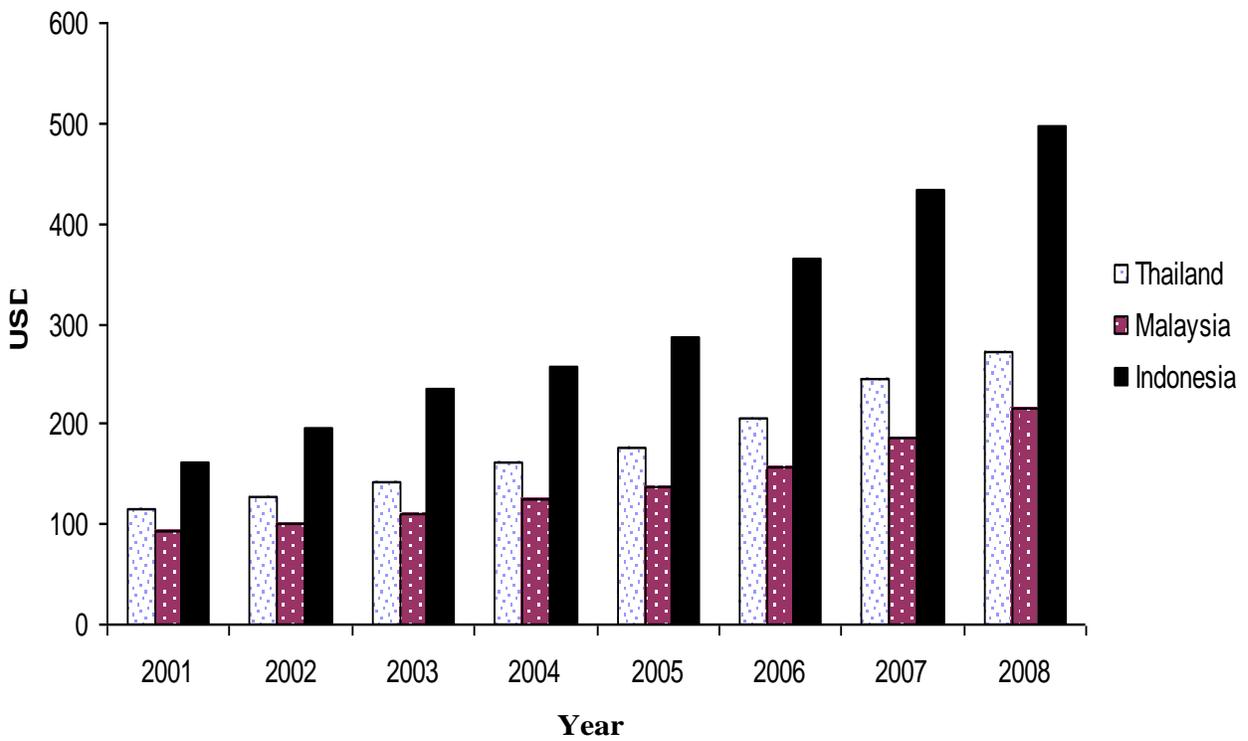
REFERENCES

- Andjelic G, Djakovic V, Radisic S (2010). Application of VaR in emerging markets: a case of selected central and eastern European countries. *Afric. J. Bus. Manage.*, 4(17): 3666-3680.
- Angeles FI, Juan AL (2004). International transmission of stock exchange volatility: Empirical evidence from the Asian crisis. *Global Finan. J.*, 15(2): 125-137.
- Baba Y, Engle RF, Kraft DF, Kroner KF (1990). Multivariate Simultaneous Generalized ARCH. Department of Economics, University of California, San Diego, Mimeo.
- Baur D (2006). A flexible dynamic correlation model, in: D. Terrell & T.B. Fomby eds., *Econometric Analysis of Financial and Economic Time Series*, Vol.1 (Amsterdam: Emerald) 3-31.
- Berndt E, Hall B, Hall, R, Hausman J (1974). Estimation and Inference in Nonlinear Structural Models. *Annals Econ. Soc.*

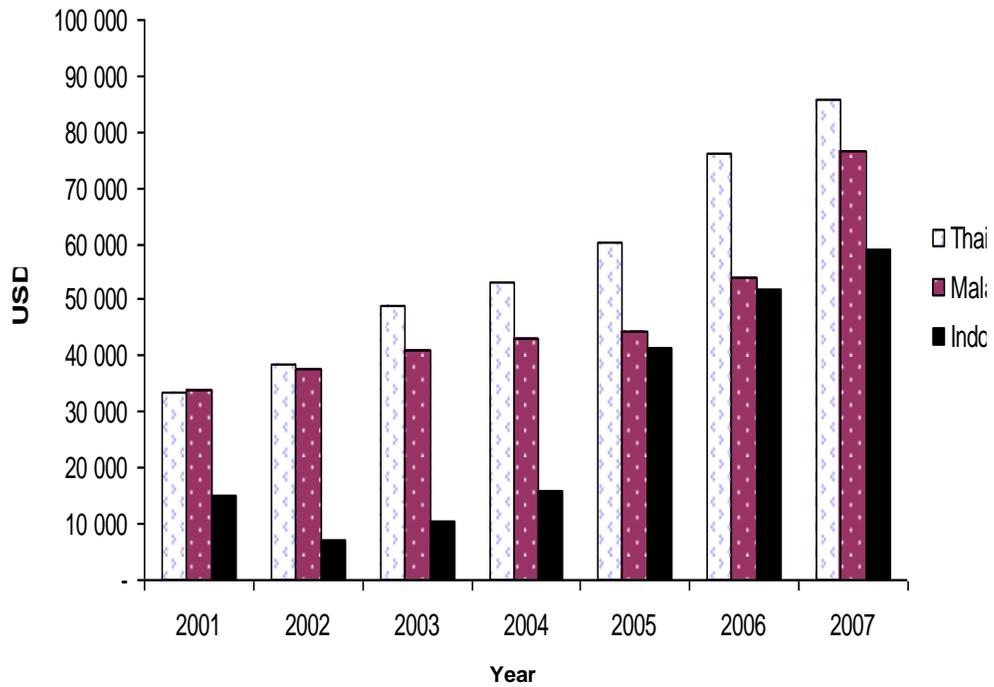
- Measure., 3: 653-665.
- Bollerslev T (1987). A Conditional Heteroskedastic Time Series Model for Speculative Prices and Rates of Return. *Rev. Econ. Stat.*, 69: 542-547.
- Bollerslev T, Engle RF, Wooldridge JM (1988). A Capital Asset Pricing Model with Time-Varying Covariances. *J. Politic. Econ.*, 96: 116-131.
- Charoenseang J, Manakit P (2002). Financial crisis and restructuring in Thailand. *J. Asian Econ.*, 13:597-613.
- Chiang TC, Jeon BN, Li HM (2007). Dynamic correlation analysis of financial contagion: evidence from Asian markets. *J. Int. Money Finan.*, 26: 1206-1228.
- Engle RF (2002). Dynamic conditional correlation: a simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *J. Bus. Econ. Stat.*, 20: 339-350.
- Engle RF, Kroner KF (1995). Multivariate Simultaneous Generalized ARCH. *Econometric Theory*. 11: 122-150.
- Engle RF, Ng V, Rothschild M, (1990). Asset pricing with a Factor-ARCH covariance structure: Empirical estimates for Treasury bills. *J. Econ.*, 45: 213-237.
- Francis I, Kim S, Yoon J, Christopher V (2001). Dynamic interdependence and volatility transmission of Asian stock markets: Evidence from the Asian. *Int. Rev. Financ. Analy.*, 10(1): 87-96.
- Glaosten L, Jagannathan R, Runkle D (1993). On the relation between expected value and the volatility of the nominal excess return on stock. *J. Finan.*, 48: 1779-1801.
- Johansson AC (2008). Interdependencies among Asian bond markets. *J. Asian Econ.*, 19: 101-116.
- Jorion P (2000). Value-at-risk: The New Benchmark for Managing Financial Risk. New York: McGraw-Hill.
- Keong LB, Yat DNC, Ling CH (2010). Month-of-the-year effects in Asian countries: A 20-year study (1990-2009). *African J. Bus. Manage.*, 4(7): 1351-1362.
- Kroner KF, Sultan J (1993). Time Varying Distribution and Dynamic Hedging with Foreign Currency Futures. *J. Financ. Quant. Analy.*, 28: 535-551.
- Kroner KF, Ng VK (1998). Modeling Asymmetric Comovements of Asset Returns. *Rev. Financ. Stud.*, 11(4): 817-844.
- Krugman P (1994). The Myth of Asia's Miracle. *Foreign Affairs.*, 73(6): 62-78.
- Krugman P (1997). Whatever happened to the East Asian Miracle? *Fortune.*, 136(4): 26-29.
- Lin SL (2010). Efficiency, productivity change and corporate value during the period of financial crisis: evidence from Asia banks. *Afric. J. Bus. Manage.*, 4(18): 3978-4002.
- Marquardt DW (1963). An Algorithm for Least Squares Estimation of Nonlinear Parameters. *Journal of the Society for Indust. Applied Math.*, 11: 431-441.
- McNiel AJ, Frey R (2000). Estimation of tail-related risk measures for heteroscedastic financial time series: an extreme value approach. *J. Empiri. Finan.*, 7: 271-300.
- Miller MH, Muthuswamy J, Whaley RE (1994). Mean reversion of Standard and Poor 500 index basis changes: Arbitrage-induced or statistical illusion? *J. Finan.*, 49: 479-513.
- Nasution A (2001). Indonesia's responses to the recent economic crisis, in: Yu, T.S and Xu, D.Q, eds., *From crisis to recovery: East Asia rising again?* (World Scientific, Singapore) 347-387.
- Sarah L (2000). Estimation of Value at risk by extreme value methods. *Extremes*. 3(2): 107-144.
- Tai CS (2007). Market integration and contagion: evidence from Asian emerging stock and foreign exchange markets. *Emerg. Mark. Rev.*, 8: 264-283.
- Tourres MA (2003). *The Tragedy That Didn't Happen*. Institute of Strategic and International Studies (ISIS) Malaysia.
- Tsay RS (2002). *Analysis of financial time series*. New York: Wiley.
- Tse YK (2000). A test for constant correlations in a multivariate GARCH model. *J. Econome.*, 98: 107-127.
- Urrutia JL (1995). Tests of random walk and market efficiency for Latin American emerging markets. *J. Financ. Res.*, 18: 299-309.
- Wang YH, Lin CT, Chen WL (2010). Does lunar cycle effect exist? Lunar phases and stock return volatilities. *Afric. J. Bus. Manage.*, 4(18): 3892-3897.
- Yu TS (2001). An overview of the financial crisis in east Asia, in: Yu, T.S and Xu, D.Q, eds., *From crisis to recovery: East Asia rising again?* (World Scientific, Singapore) 1-29.
- Zakoian JM (1994). Threshold heteroskedasticity models. *J. Econ. Dynam. Control.*, 15: 931-955.



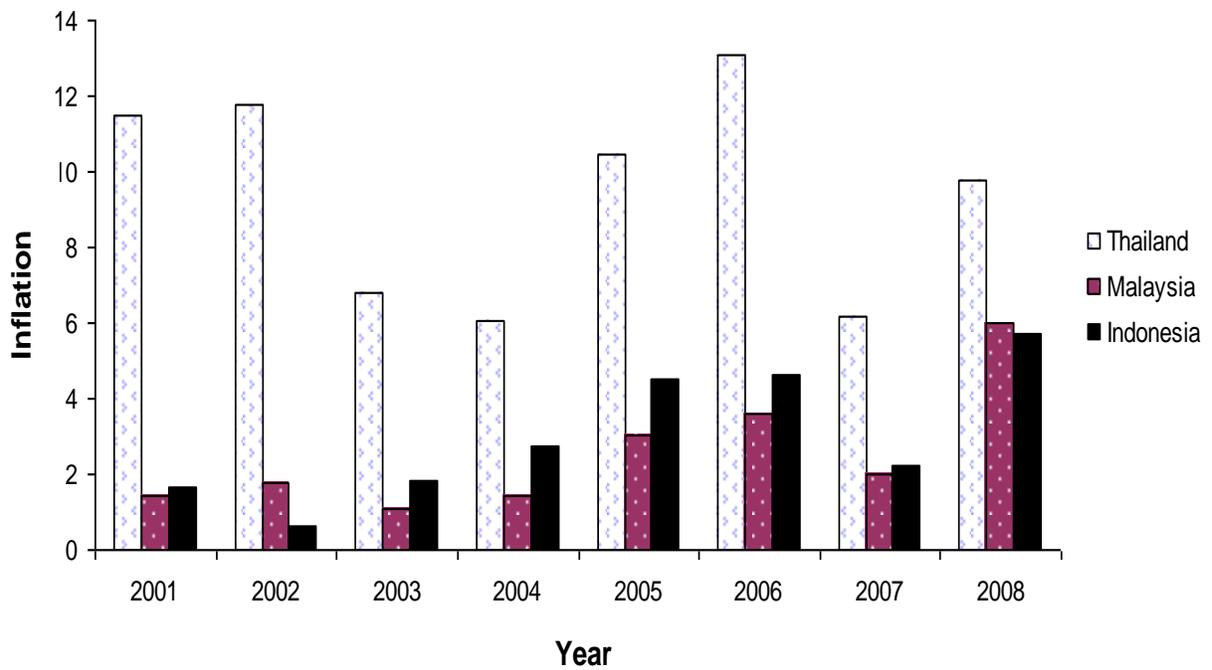
Appendix A. Gross domestic product based on purchasing-power-parity (PPP) per capita GDP. Source: The IMF.



Appendix B. Gross domestic product, current prices (billion unit). Source: The IMF.



Appendix C. The foreign direct investment (FDI) in million unit.
Source: The United Nations Conference on Trade and Development (UNCTAD).



Appendix D. Inflation rate.
Source: The IMF.