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Dynamic linkages between China and US equity markets under two recent financial crises

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ABSTRACT

This paper explores and compares the effects of two financial crises (the 1997 Asian Financial Crisis and the 2007-2010 Subprime Financial Crisis) on short-run and long-run linkages between equity markets in China (mainland and Hong Kong) and US. In particular, we not only investigate the return causality relationships by applying vector autoregressive (VAR) analysis, but we also examine the volatility spillover effects by using a multivariate GARCH - BEKK model. The empirical findings indicate that, although the financial markets in mainland China have gradually opened and become more liberalized, the mainland stock indices are not cointegrated with US and Hong Kong in the long run. However, in the short run, the spillover effects on return and volatility exist between different groups of equity markets. Overall, compared to the Asian Crisis, the dynamic interactions between China and US have increased during the Subprime Crisis.

Key Words: Equity markets linkages, Financial Crisis, Return causality, Volatility spillovers, MGARCH – BEKK model.

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1. Introduction

Currently, the financial markets in both mature and emerging economies are experiencing extensive deregulation and liberalization. Computer technology as well as the innovation of the financial products is also developing quite rapidly. All these factors promote the global equity markets integration. Meanwhile, in the past decades, the events of the financial crises have frequently happened, and every financial crisis is the turning point of economic cycle. For instance, 1987 Black Monday, 1991 Japanese asset price bubble collapse, 1997 Asian Financial Crisis, 2001 dot com bubble and 2007-2010 Subprime Financial Crisis. Against these backgrounds, the topic about the dynamic linkages among different stock markets has received great attention.

When referring to international equity markets integrations, researchers usually examine the cross-country interactions in both short-run and long-run. Moreover, they not only investigate the return causality linkages, but volatility spillovers effects. The findings about dynamic links among different stock markets are important for numerous reasons. Firstly, the fundamental argument of Capital Asset Pricing Model (CAPM) suggests that the market risk of the asset is not able to be eliminated. Therefore, whether investors can diversify risk by investing in the multinational equities largely depends on the degree of comovements among different stock markets. Secondly, if the returns causality exists among different stock indices, investors can exploit trading strategy to get profit even during financial turbulent periods. Thirdly, information about volatility spillover effects help to price options and optimize portfolios. Under financial crises, the discovery of volatility spillover is useful for the application of value at risk and hedging strategies. Finally, the assessment about the cross-country integration helps policy makers to monitor the potential for the financial contagion and control international capital flows, and finally make effective regulations to stabilize international financial system (Ng 2000).

Generally, three approaches are popular as measuring the transmission of return and volatility spillovers among different stock markets. Correlations analysis, Vector autoregressive (VAR) and related econometrics approaches and Multivariate GARCH model. The stock markets comovements among developed countries have been widely studied. However, with the role of the emerging markets becoming more important, a number of literatures begin to investigate the relationships between the developed and emerging markets. Worthington and Higgs (2004) analyze the transmission of equity returns and volatility in Asian developed markets (namely, Hong Kong, Japan and Singapore) and emerging markets (Indonesia, Korea, Malaysia, the Philippines, Taiwan and Thailand) during the 15 January 1988 to 6 October 2000. They identify the source and magnitude of the spillovers by using MGARCH and demonstrate that the mean spillovers from the developed to emerging markets are not homogeneous across the emerging markets, and the own-volatility spillovers are generally higher than cross-volatility spillovers for

all markets, but especially for the emerging markets. Li (2007) utilizes multivariate GARCH approach to examine the linkages between the stock markets in China mainland and Hong Kong and US, respectively. And he finds out the Chinese mainland stock markets have closed linkages in terms of return and volatility with the regional developed market in Hong Kong, but have no direct interactions with the global financial center US. Ping and Peijie (2005) investigate the stock market linkages between Greater China (China mainland, Hong Kong and Taiwan) and the US and Japan in terms of price and volatility spillovers by applying GJR-BEKK GARCH model. Their findings suggest that the volatility spillovers have been found between these markets, but are very weak and the price spillovers appear too weak to be discernable. Liu and Pan (1997) examine the mean return and volatility spillover effects from the US and Japan to Hong Kong, Singapore, Taiwan, and Thailand. Their finding suggests that the US market is more influential than the Japanese market in transmitting returns and volatilities to the four Asian markets. By using a vector autoregressive (VAR) analysis, Liu et al. (1998) investigate the dynamic structure of six national equity markets (the US, Japan, Hong Kong, Singapore, Taiwan, and Thailand). They conduct the tests using the daily stock returns from January 2, 1985 through December 31, 1990. Their results indicate that the degree of the integration among different equity markets has increased after the 1987 stock market crash; and the US market plays a dominant role in influencing the Pacific-Basin markets; Japan and Singapore together have a significant and persistent impact on the other Asian markets. Miyakoshi (2003) examines how and to what extent the return and volatility spillovers of the Asian markets are influenced by the regional market – Japan and the international market – the US by dealing with the US shocks as an exogenous variable in the bivariate EGARCH models for some Asian markets (Korea, Taiwan, Singapore, Thailand, Indonesia, Malaysia, Hong Kong and Japan). The selected sample period ranges from 1 January 1998 to 30 April 2000. He finds the evidence that the returns in the Asian markets are only influenced by the US, but the volatility in the Asian markets is influenced more by the Japanese market than the US market.

Although some literatures study the linkages between mature and emerging financial markets, they focused more on the transmission mechanisms during the normal times than the turbulent times. Besides the interactions between the emerging and developed markets, the recent studies begin to pay much more attention on the equity markets integrations during the financial crises. By applying a cointegrated vector autoregression (VAR) framework, Yang and Kolari (2003) examine the long-run cointegration and the short-run causal dynamics between ten Asian emerging countries and the U.S and Japan during Asian Financial Crisis. And they indicate that the U.S influenced the Asian emerging markets substantially, but US stock markets are almost unaffected by Asian markets. Tao (2009) concentrates on the spillover effects from U.S to China mainland and Hong Kong during Subprime Crisis by applying both the univariate and multivariate GARCH models. They find the evidence that the spillover effects from US to Hong Kong are much stronger than China mainland. But the impact of the volatility from the United States on China's stock markets has been more persistent than that from HK. Diebold Francis and

Yilmaz (2009) examine how the recent US crisis makes influence on the volatility transmission from the U.S stock market to the major stock markets in South East Asian (Singapore, Hong Kong, Korea, Taiwan, Malaysia, Thailand and Indonesia). They adopt a bivariate GARCH-BEKK model and find the evidence of volatility spillovers from US to South East Asia, but the degree of persistence and reversion vary across countries. Furthermore, Singapore, Korea and Hong Kong are among the most South East Asia markets vulnerable to shocks originating from US.

The purpose of this research is to explore and compare the effects of two financial crises (1997 Asian Financial Crisis and 2007-2010 Subprime Financial Crisis) on the dynamic linkages between equity markets in China (mainland and Hong Kong) and US. More specifically, this paper investigates the return and volatility interactions between China and US stock markets, and then tests the hypothesis whether with the gradual openness of the mainland China stock markets, the mainland stock markets are influenced more by the US stock markets. Meanwhile, this paper attempts to answer the following questions by applying several econometrics approaches:

Q1. Have China's stock markets cointegrated with the US stock market in the long run?
Q2. Do return and volatility spillover effects among different equity markets exist in short run?
Q3. How do return and volatility spillover effects change during the two crises?

We seek to contribute to the existing literatures about this issue in two ways. First of all, this paper provides the compressive analysis about the stock markets interactions between China and US both on the short-term and long-term aspects. Moreover, we investigate the markets dynamic links not only in term of the first moment (mean return), but also the second moment of the stock returns (i.e. the feature that the conditional variance of the stock return is time-varying). Secondly, with the development of China's economy, the stock markets in the mainland become much more mature. However, the related literatures about dynamic linkage between mainland markets and developed markets are inadequate. This paper fills this gap.

The remainder of this paper is organized as follows. Section 2 introduces the features of Chinese stock indices against Hang Seng index in Hong Kong and then outlines the background of Asian Financial Crisis and US Subprime Financial Crisis. Section 3 discusses the methodological design. Section 4 describes the data design and the preliminary analysis. Section 5 reports the empirical results and further discusses their implications. Finally, Section 6 concludes.

2. Background

2.1 Structure of Chinese Stock Markets

In this paper, China stock markets include the market in mainland China and Hong Kong. Although these markets are closely linked because of political and economical ties, they vary in terms of the degree of openness, maturity and transparency. The stock markets in mainland China are relative young and immature which was established in the early 1990s. But they indeed have been considered as one of the fastest growing emerging markets and became the second largest market in Asia, just behind Japan.

The stock exchanges in mainland China consist of Shanghai Stock Exchange (SHSE) and Shenzhen Stock Exchange (SZSE). There are two main differences between SHSE and SZSE. Firstly, SHSE is the largest stock exchange market in mainland China and headquartered in Shanghai city, which is the largest city and one of the financial centers in mainland. SZSE is located in Shenzhen city, which is the first and the most important special economic zone in China which neighbors Hong Kong. Secondly, most companies listed on SHSE are large and stated-owned. And they are more closely monitored by the Chinese government. By contract, SZSE are mainly dominated by small and export-oriented firms. Many of them are the joint venture enterprises with close relations to the firms in Hong Kong. Considering these characteristics, SHSE may be sheltered from global economic turmoil, but SZSE are more vulnerable to a worldwide financial turbulence (Wang and Liu 2004).

The most notable feature of the stock exchanges in mainland China is that two types of shares are traded on SHSE and SZSE respectively, which are class A-shares and class B-shares. A-shares were originally meant for the domestic investors and are listed in the denomination of the Chinese local currency Renminbi or RMB. But after the implementation of the reforms in Dec 2002, foreign institutional investors have been permitted to invest in A-shares under the system of QFII (Qualified Foreign Institutional Investor)[1]. B shares were originally designated for the foreign investors and are denominated and traded in US dollars on the SHSE and Hong Kong dollars on the SZSE. Chinese residents were not allowed to buy and sell the B-shares since the Chinese laws did not allowed the domestic residents to freely exchange the foreign currencies. But since 2001, the domestic investors are also allowed to buy and sell the B-shares[2]. Here two points should be noted. Firstly, the B-share markets have not expanded as fast as A-share markets in terms of the number of the listed companies, market capitalization and trading volume. For instance, until the year 2004, the listed companies of A-share and B-share on SHSE are 827 and

[1] The QFII are defined as overseas fund management firms, insurance companies, securities companies, and other asset management institutions that must be approved by China Securities Regulatory Commission (SRC) to invest in China's securities market and are granted investment quotas by the State Administration of Foreign Exchange. (More details, see Lin (2006) pp56)

[2] . "http://www.economywatch.com/market/share-market/world/china.html."

54, respectively. The listed companies of A-share and B-share on SZSE are 522 and 56, respectively (Lin 2006). Secondly, the QFII candidate must be qualified for a series of strict standards. Until February 2009, a total of 79 foreign institutional investors have been approved under the QFII program, which indicates that the financial markets in mainland China is only open to minority part of foreign investors, and most foreign investors are limited (http://en.wikipedia.org/wiki/Qualified_Foreign_Institutional_Investor).

The Hong Kong Stock Exchange (HKSE) was established in 1891 and is the third largest stock market in Asia, just behind Japan and Shanghai. The shares listed on HKSE are open for both domestic and foreign investors. Hong Kong is an important financial center in Asia, and also plays a key role as a channel for imports and exports from mainland China. Thus Hong Kong is closely integrated to the mainland Economy, especially after Hong Kong returning to mainland China in 1997.

2.2 Two financial crises

2.2.1 Asian Financial Crisis

High rates of investment and outstanding rates of export growth generated the rapid development of economies in East and Southeast Asia. Thailand, Malaysia, Indonesia, Singapore, and South Korea experienced high growth rates, 8–12% GDP in the late 1980s and early 1990s. East Asian economic miracle became commonplace. However, the combination of slow export growth and competition of export from mainland China resulted in large current account deficits in Thailand. Thailand's current account deficit rose to the 8 percent of GDP in 1996 (http://www.adb.org/Documents/Books/Key_Indicators/2003/pdf/rt29.pdf). Later, the Thai authority didn't peg the baht to the US dollar. Numerous international investors had large short positions against Thai baht. The baht depreciated at an alarming rate. By the end of 1997, the baht had lost nearly 50 percent of its value against the US dollar. Coupled with the devaluation of Thai baht, Asian Financial Crisis started in July 1997.

The financial crisis in Thailand rapidly spread to other economies in Southeast Asia through trade channel. At the first half of 1998, the stock markets mal-performed as the depreciation of currency in the neighboring countries including Indonesia, Malaysia, Philippines and South Korea. During this period, speculators attacked Hong Kong dollar, Korean won and the Taiwanese dollar. The stock markets of these areas were in turmoil because of the speculations (Ratanapakorn and Sharma Subhash 2002). Millions of dollars in the stock markets evaporated, and the continued deterioration of financial conditions had strongly negative impacts on investors' confidence. The emerging stock markets in Southeast Asia were in a compete turmoil.

As the crisis spread, financial contagion effects not only attacked the financial markets but also hit the real economies. Since August 1998, the real economy of Russia and Brazil were hurt by

the shock. Later, these negative shocks in the real GDP growth were transferred to Latin American economies. Asian Crisis raised the fears in the worldwide economy (Fernandez-Izquierdo and Lafuente Juan 2004).

In summary, the causes of Asian Financial Crisis are summarized by three elements: modest macroeconomic imbalances, financial sector weakness and mismanagement of the maturity structure of short term debt (Eichengreen 2003). However, compared to other countries in East and Southeast Asia, mainland China was relatively insulated, although China also suffered a slow GDP growth. There are two reasons to explain it. One is most of China's foreign investment took the form of factories rather than equities. The other is the stock markets in mainland China are segmented and immature.

2.2.2 Subprime Financial Crisis

After suffering from 911, the US Federal Reserve adopted a low interest rate to recover the downturn economy. The large foreign capital inflows with low interest rate created an easy credit condition in the United States. These two factors contributed to both housing and credit bubbles in the US (Chen, Huang et al. 2010). As part of the housing and credit booms, mortgage lenders tend to lend more loans to borrowers, even those with poor credit records. Meanwhile the number of related financial derivatives increased dramatically during this period, such as mortgage-backed securities (MBS). With the rising interest rates of loans over time, houseowners repaying their mortgage payments had a harder and harder time. At the same time, a decrease in housing price resulted in the values of the real property being less than the mortgage loans in 2006. Both factors forced borrowers to enter foreclosure. More and more mortgage companies faced the risk of bankruptcy since MBS derived their value from mortgage payments and housing prices. In order to get rid of this dilemma, investment banks and mortgage companies securitized the subprime mortgage loan which was called collateralized debt obligation (CDO). And they issued and sold CDOs to financial institutional investors in foreign countries. Such financial innovation tied institutions and investors around the world to the US.

The burst of housing booms accompanied the collapse of subprime loan market in the United States, leading to the credit crunch in July 2007. This financial crisis in US spread from housing markets to credit markets and mushroomed into a global financial crisis by September 2008. The Subprime Financial Crisis is regarded as the most serious crisis since the Great Depression (Kenc and Dibooglu 2010). At the beginning of the crisis, at least 100 mortgage companies shut down (Onaran 2008). As the crisis deepened, about $750 billion in subprime MBSs had been lost around the world (Onaran 2008). When those institutional investors could not afford huge losses, they had to go bankrupt. Lehman Brothers failed in September 2008. Subprime Financial Crisis reached the peaking point. Until October 2008, about US$25 trillion had been erased from the value of stock markets (Naudé 2009).

Subprime Financial Crisis not only hits the financial institutions but also makes investors suffer psychological shock. To avoid further loss, the US investors took back funds from Asia and other emerging market, and then they transferred investment to their local markets. Most emerging market suffered from these activities. However, China was sheltered from the worst of Subprime Crisis although China's stock markets was not immune to the contagion's spillover effects (D 2009).

3. Methodology

This paper investigates the dynamic linkage between China and US stock markets under the two recent financial crises. And the following econometric approaches are applied, including unit root tests, cointegration, Granger-causality, variance decomposition, impulses analysis and Multivariate GARCH model. Unit root tests are conducted first since the stationary property of a series is the premise for the other techniques. The cointegration test measures the relationships between different equity markets in the long run while the other three tests (Granger-causality, variance decomposition and impulses analysis) are utilized to examine the short-run aspects. If cointegration is found, it means even if a set of variables are non-stationary, they never drift apart in the long run. In contrast, if they have a lack of cointegration, they have no long - run links. If cointegration exists, the Granger-causality, variance decomposition and impulses analysis must be constructed on the error-correction models. If no cointegration is found, then the analyses are based on the regression of the first differences of the variables by utilizing a standard VAR framework. The Granger-causality identifies the direction of the causality while the variance decomposition and impulses analysis examines the durations and speed of the interactions between equity markets. The volatility spillovers are measured by adopting the multivariate GARCH- BEKK model. This approach provides us the spillovers and the fluctuations of the conditional correlations between China and US stock market returns over time.

3.1 Unit root and stationary tests

Many time series exhibit trend or non-stationary behavior. These characteristics are especially evident in the financial time series such as indices of stock price. If a series is non-stationary, and unless it combined with other non-stationary series to form a stationary cointegration relationship, then the regressions involving the series can cause the spurious regression. Many approaches can be performed to examine the stationarity of time series data. But the most popular approaches are Augmented Dickey-Fuller (ADF) test, Phillips-Perron test (PP), Kwiatkowski, Phillips, Schmidt, and Shin (KPSS, 1992) test. Because of the fact that the ADF and PP tests usually give us the same conclusion, we only perform the ADF test and KPSS test in this paper.

3.1.1 Unit Root Test - Augmented Dickey-Fuller (ADF) test

The Augmented Dickey-Fuller (ADF) test is developed by Dickey and Fuller and there are three main versions which can be used to test for the presence of unit roots.

1. Test for a unit root

$$\Delta y_t = \varphi^* y_{t-1} + \sum_{i=1}^{p-1} \varphi_i \, \Delta y_{t-i} + u_t$$

2. Test for a unit root with drift

$$\Delta y_t = \beta_0 + \varphi^* y_{t-1} + \sum_{i=1}^{p-1} \varphi_i \, \Delta y_{t-i} + u_t$$

3. Test for a unit root with drift and deterministic time trend

$$\Delta y_t = \beta_0 + \varphi^* y_{t-1} + \sum_{i=1}^{p-1} \varphi_i \, \Delta y_{t-i} + \beta_1 t + u_t$$

Where y_t denotes the log price of stock index or log return of stock index at time period t and $\Delta y_t = y_t - y_{t-1}$. β_0 is the drift term, t is linear trend term and u_t is the error term.

H_0: $\varphi^* = 0$ Non-stationary

H_1: $\varphi^* < 0$ Stationary

The null hypothesis is that a series does contain a unit root (non-stationary process) against the alternative of stationary. To test for the presence of a unit root, we need to calculate the T-statistic $\tau = \frac{\varphi^*}{\sqrt{\text{var}\,(\varphi^*)}}$ and then compare it to the corresponding critical value at different significant level. If the null hypothesis is rejected, it is concluded that a series y_t which includes drift, trend or none doesn't contain a unit root.

However, to perform Augmented Dickey-Fuller (ADF) test, firstly we need to specify whether to include a constant, a constant and a linear trend, or neither in the test regression. One approach would be to run the test with both a constant and a linear trend since the other two cases are just special cases of this more general specification. However, including irrelevant regressors in the regression will reduce the power of the test to reject the null of a unit root**.** To overcome this

problem, the form of test regression can be based upon the graphical inspection of a series (Verbeek 2004). If the plot of the data does not start from the origin, then the estimation equation should include a constant. If the plot of the data indicates the apparent upward or downward trend, then the trend term should be contained in the regression.

Furthermore, it is also very important to select the appropriate number of lagged difference term *p*. Too few lags may lead to the over rejecting the null hypothesis when it is true, while too many lags may reduce the power of the test to reject the null. One suggested solution is based on Information criteria such as Akaike Information Criterion (AIC), the Schwartz Bayesian Criterion (SBIC). In other words, we determine the appropriate lag length which minimizes the information criteria. If we get the contradictive results from AIC and SBIC, SBIC criterion is preferred in this paper. The reason is that SBIC will select the correct model with few lags, while on average AIC will choose the model with too many lag orders.

The main criticism of the Augmented Dickey-Fuller (ADF) test is the power of the test is very low if the process is nearly non-stationary which means the process is stationary but with a root close to the non-stationary boundary (Brooks 2002).

3.1.2 Stationary Test - Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) test

To circumvent the limitation that ADF test always has a low power, Kwiatkowski, Phillips, Schmidt, and Shin (1992) proposed an alternative test which y_t is assumed to be stationary under the null. The KPSS test is a Lagrange multiplier test and the test statistic can be computed by firstly regressing the dependent variable y_t on a constant or a constant and a time trend t. And then save the OLS residuals ε_t and compute the partial sums $\mathrm{S_t} = \sum_{\mathrm{s}=1}^{\mathrm{t}} \varepsilon_{\mathrm{s}}$ for all t. Further the test statistic is given by (Verbeek 2004):

$$KPSS\ LM = \sum_{t=1}^{T} \frac{S_t^{\ 2}}{\hat{\sigma}_{\varepsilon}^{\ 2}}$$

where $S_t = \sum_{s=1}^{t} \varepsilon_s$ and $\hat{\sigma}_{\varepsilon}^{\ 2}$ is the estimated error variance from the regression

$$y_t = \alpha + \varepsilon_t \ \text{ or } \ y_t = \alpha + \beta t + \varepsilon_t$$

For the conclusion to be robust, we use the unit root test and the stationary test jointly. The results of these two tests can be compared and see if the same conclusion is obtained. If the contradictive results are reached based on both ADF and KPSS tests, KPSS test is preferred due to the drawbacks of ADF tests.

3.2 **Vector autoregressive (VAR) models** (Brooks 2002)

Vector autoregressive (VAR) models are proposed by Sims 1980 and can be used to capture the dynamics and the interdependency of multivariate time series. It is regarded as a generalization of univariate autoregressive models or a combination between the simultaneous equations models and the univariate time series models.

The simplest case is the bivariate VAR which contains two variables [y_{1t}, y_{2t}]. The current values depend on the previous values of y_{1t} and y_{2t} and error terms. This can be written as:

$$\begin{pmatrix} y_{1t} \\ y_{2t} \end{pmatrix} = \begin{pmatrix} \beta_{10} \\ \beta_{20} \end{pmatrix} + \begin{pmatrix} \beta_{11} & \alpha_{11} \\ \alpha_{21} & \beta_{21} \end{pmatrix} \begin{pmatrix} y_{1t-1} \\ y_{2t-1} \end{pmatrix} + \begin{pmatrix} u_{1t} \\ u_{2t} \end{pmatrix}$$

Where u_{it} is a white noise term with E (u_{it}) = 0, E ($u_{1t}u_{2t}$) =0.

The system above can also be extended to contain g variables y_{1t} , y_{2t} ,.....y_{gt} , and each current value depends on the different combinations of the previous k values of g variables and error terms.

VAR models are more flexible and easy to use for analyzing the multiple time series because the researchers need not to specify which variables are endogenous or exogenous. But there are still some weaknesses. Firstly, it is hard to see which variables have significant effect on the dependent variable. Secondly, VAR models require that all the variables in the system should be stationary. However, most financial series have a feature of the non-stationarity. Thus VAR should be transformed into a Vector Error Correction Model (VECM) which releases the stationarity requirement of data by the reason that the VECM includes first difference terms and cointegration relationships. Finally, it is not easy to determine the appropriate lag lengths. But the problems can be solved by several approaches.

To select the optimal lag length, two methods are broadly applied. One way is a likelihood ratio test, and the other is the information criteria, such Akaike's (AIC) and Schwarz's Bayesian Information Criteria (SBIC). The best model is the one that maximize LR, or minimize the information criteria. Compared with LR ratio test, the information criteria method is more powerful. If AIC and SBIC suggest the contradictive lag length, SBIC criterion is preferred in this paper. The reason is that SBIC will deliver the correct model with few lags, While on average AIC will choose a model with too many lag orders.

3.3 The Johansen technique based on VAR

3.3.1 The Johansen Approach

The concept of cointegration is developed by Engle and Granger. If two or more series are themselves non-stationary, but a linear combination of them is stationary, then the series is said to be cointegrated.

Generally, two approaches are broadly applied to test cointegration. One is Engle-Granger test which is only used to a single series. An alternative is the Johansen approach that is suitable for a multivariate case. The Johansen setup permits the test of hypotheses about the long-run equilibrium between the variables. In order to investigate the relationship of stock index between China and US, the Johansen cointegration technique is used in this study.

The Johansen test is extended by the vector autoregression (VAR) of order k given by (Hjalmarsson and Osterholm 2007):

$$\boldsymbol{Y_t} = \mu + \boldsymbol{\beta_1 Y_{t-1}} + \boldsymbol{\beta_2 Y_{t-2}} + \cdots + \boldsymbol{\beta_k Y_{t-k}} + \boldsymbol{u_t}$$

where $\boldsymbol{Y_t}$ is an $N \times 1$ column vector of dependent variables which are integrated of order one.

$\boldsymbol{u_t}$ denotes an $N \times 1$ column vector of innovations.

Before applying the Johansen test, the VAR models should be transformed into a vector error correction model (VECM) of the form:

$$\Delta \mathbf{Y_t} = \boldsymbol{\Pi} \mathbf{Y_{t-k}} + \boldsymbol{\Gamma_1} \Delta \mathbf{Y_{t-1}} + \boldsymbol{\Gamma_2} \Delta \mathbf{Y_{t-2}} + \cdots + \boldsymbol{\Gamma_{k-1}} \Delta \mathbf{Y_{t-k+1}} + \mathbf{u_t}$$

Where $\Pi = \left(\sum_{i=1}^{k} \beta_i\right) - I_n$ and $\Gamma_i = \left(\sum_{j=1}^{i} \beta_i\right) - I_n$

If r (the number of linearly independent combinations of the variables in $\mathbf{Y_t}$) is equal to N (the number of column vectors of $\mathbf{Y_t}$), it means Π is full rank. If Π is less than full rank, $\Pi = \alpha * \beta'$ where both α and β are an (n× r) matrix. In other words, the coefficient matrix Π is a product of α and β. The element of α indicates the speed of the adjustment to equilibrium, while β can be interpreted as a long-run coefficient matrix.

3.3.2 Testing for the rank of Π matrix

The Johansen test examines whether the restrictions implied by the rank of Π matrix can be rejected (Huyghebaert and Lihong 2010). The rank of a matrix is equal to the number of its eigenvalues which are different from zero. The eigenvalues are denoted by λ_i. If the variables are not cointegrated, the rank of Π will not be significantly different from zero, i.e. $\lambda_i \approx 0$.

Two likelihood ratio tests are suggested by Johansen, which are formulated as:

$$\lambda_{trace}(r) = -T \sum_{i=r+1}^{n} \ln(1 - \hat{\lambda}_i)$$

and $$\lambda_{max}(r, r+1) = -T \ln(1 - \lambda_{r+1}).$$

where T is the sample size and λ is the eigenvalues.

The null hypothesis of at most r cointegrating vectors against the alternative hypothesis of more than r cointegrating vectors is tested by trace statistics. The null hypothesis of r cointegrating vector against the alternative of r+1 is tested by maximizing eigenvalues statistic (Singh, Kumar et al. 2009).

However, if two test approaches give us different conclusions, which one would we trust? Helmut and Pentti (2001) found that there is a difference between them when the sample size is small. They applied the Monte Carlo experiment to compare trace test statistics with max-eigenvalues statistics. The result shows the power of trace tests is superior to that of the maximum eigenvalues tests. Thus, when there is an apparent contradiction in two tests for cointegration rank, the trace test is much more reliable.

3.3.3 The selection of deterministic components in the Johansen test (Harris and Sollis 2003)

3.3.3.1 The deterministic components in the multivariate model

When the researchers implement the Johansen test, the deterministic components should be identified, such as whether deterministic components are contained in levels of data or cointegration equation. For illustration, consider the following VECM form which contains the various options:

$$\Delta Y_t = \Gamma_1 \Delta Y_{t-1} + \alpha \begin{pmatrix} \beta \\ \mu_1 \\ \delta_1 \end{pmatrix} Y_{t-k} + \alpha\mu_2 + \alpha\delta_2 t + u_t$$

There are five different models in accordance with Eviews 7.0 options

Model 1: There is no deterministic trend in data and no intercept or trend in cointegration equations (CE), i.e. $\delta_1 = \delta_2 = \mu_1 = \mu_2 = 0$

Model 2: There is no linear trend in data but an intercept (no trend) in CE, i.e. $\delta_1 = \delta_2 = \mu_2 = 0$.

Model 3: There is a linear trend in data and intercept (no trend) in CE, i.e. $\delta_1 = \delta_2 = 0$.

Model 4: There is a linear trend in data, while intercept and trend exist in CE, i.e. $\delta_2 = 0$.

Model 5: There is a quadratic deterministic trend in data, intercept and trend in CE.

In practice, Model 1 and 5 are rarely used. Model 1 is unlikely to occur in real world except all financial series have zero mean. Model 5 induces implausible out-of-sample forecasts. Thus, only the model 2-4 would be considered.

3.3.3.2 Pantula principle

Generally, the graph of the vector y_t is plotted to decide the deterministic component. However, the plots of the data would provide little information about the selection of models. Johansen suggested the need to test the joint hypothesis of both the rank order and the deterministic components. This method is called Pantula principle.

All three models are estimated and the results are presented from the most restrictive alternative (like r = 0 and Model 2) to the least restrictive alternative (i.e. r = n-1 and Model 4). The process of Pantula principle is to move from the most restrictive model to the least restrictive model and then to compare the trace test statistic to its critical value at each stage. The test is completed when the null hypothesis is not rejected at the first time.

3.4 Granger causality test

Granger causality is different from causality. For instance, the causality from A to B indicates that A causes B directly. Granger causality is an econometrics tool based on the standard F-test framework to determine whether one time series is useful to predict the future of another series. A variable X Granger-causes Y if the past changes of X could help to predict current changes of Y. If X Granger-causes Y and not vice versa, it is called unidirectional causality. If X Granger causes Y and Y also Granger causes X, it would be said that there is bi-directional causality between. (Brooks 2002).

When we conduct Granger causality tests, two cases should be considered depending on whether the variables are cointegrated or not.

(a) If the variables are not cointegrated, the following VAR estimation equations in the first differences are tested.

$$\Delta Y_t = \sum_{j=1}^{n} b_j \, \Delta X_{t-j} + \sum_{j=1}^{n} c_j \, \Delta Y_{t-j} + u_{t-1}$$

$$\Delta X_t = \sum_{j=1}^{n} b_j^* \, \Delta Y_{t-j} + \sum_{j=1}^{n} c_j^* \, \Delta X_{t-j} + u_{t-1}^*$$

(b) If the variables are cointegrated, the following error correction models (ECM) are tested.

$$\Delta Y_t = \sum_{j=1}^{n} b_j \, \Delta X_{t-j} + \sum_{j=1}^{n} c_j \, \Delta Y_{t-j} + \varphi e_{t-1} + w_t$$

$$\Delta X_t = \sum_{j=1}^{n} b_j^* \, \Delta Y_{t-j} + \sum_{j=1}^{n} c_j^* \, \Delta X_{t-j} + \varphi e_{t-1}^* + w_t^*$$

Let ΔY_t and ΔX_t denote the stock returns of country x and country y, respectively. e_{t-1} and e_{t-1}^*, are the lagged residuals from two equations in case (a).The null hypothesis for the Granger test in the above equations is *X* does not cause *Y* (all $b_j = 0$); the alternative is X causes Y (at least one $b_j \neq 0$ and all $b_j^* = 0$). If the null hypothesis is rejected, the conclusion that X Granger- causes Y is obtained (Roca 1999).

The reason to use ECM to test the causality between cointegrated variables is that regressing on the first difference cointegrated variables could lead to misspecification error.

It should be noted that Granger-causality really represents only a correlation between the current value of one variable and the previous values of others. It doesn't mean that movements of one variable cause movements of another (Brooks 2002). Moreover, although causality in VAR examines whether the current value of variable X can be explained by the past values of variable Y, it still does not explain the sign of the relationship or how long these effects last. However, further information will be given by impulse responses and variance decomposition analysis.

3.5 Impulse responses and Variance decomposition

Generally, an impulse response indicates the reaction of any dynamic system in response to some external changes. In particular, VAR's impulse responses mainly examine how the dependent variables react to shocks from each independent variable. The accumulated effects of unit impulses are measured by appropriate summation of the coefficients of the impulse response functions (Lin 2006). However, Lutkepohl and Reimers (1992) stated that the traditional impulse response analysis requires orthogonalization of shocks. And the results vary with the ordering of the variables in the VAR. The higher correlations between the residuals are, the more important the variable ordering is. In order to overcome this problem, Pesaran and Shin (1998) developed the generalized impulse response functions which adjust the influence of a different ordering of the variables on impulse response functions. The generalized impulse responses are plotted by

using historical patterns of correlations. This paper only shows the graph of each financial series in response to various shocks. It doesn't refer to any calculation about the generalized impulse response functions.

However, if VAR models include more equations or more lags, it is hard to observe the effects of external shocks on the variables. In order to show the interactions between the equations, variance decompositions analysis would be applied.

Variance decompositions trace out the proportion of the movements in the dependent variables that are due to their own shocks versus shocks to the other variables (Brooks 2002). It shows the components of variances of dependent variables clearly. Meanwhile, variance decomposition analysis is also a powerful tool to predict the changes of financial series in future. But this is not our subject. Thus, we just regard variance decomposition as a confirmation of impulse responses. Generally, impulse responses analysis and variance decompositions offer very similar information.

3.6 Multivariate GARCH model

3.6.1 Multivariate GARCH model

In conventional econometrics models, the variance of the error terms is assumed to be constant (homoskedasticity) over time. But it is unlikely in the context of the financial time series. Many financial time series have exhibited the property of 'long-memory' (the presence of statistically significant correlations between observations that are a large distance apart) (Harris and Sollis 2003). Another distinguishing feature of the financial time series is known as 'volatility clustering', i.e. large (small) volatility followed by large (small) volatility. In other words, the current level of the volatility is positive with its level during the immediately preceding periods (Brooks 2002).

Engle (1982) developed the ARCH (Autoregressive Conditional Heteroscedasticity) model that allows for the conditional variance to be time-varying. However there are some limitations for ARCH (q) model. Bollerslev (1986) extended the ARCH model to a more general one – GARCH (Generalized Autoregressive Conditional Heteroscedasticity), which allows for the conditional variance to be dependent upon previous own lags.

However, some researchers are interested in quantifying the interactions between the volatility of *N* different financial time series. In this context, the multivariate GARCH models are utilized instead of univariate counterparts. In multivariate GARCH models, considering a stochastic vector series r_t with a dimension of $(\mathrm{N} \times 1)$, the conditional mean of r_t is an $(\mathrm{N} \times 1)$ vector μ_t and the conditional covariance of r_t is an $(\mathrm{N} \times \mathrm{N})$ matrix $\mathrm{H_t}$. Let $\mathrm{I_{t-1}}$ denotes the information set generated by the past information until time t-1 and θ is a finite vector of parameters (Bauwens, Laurent et al. 2006).

$$\mathrm{r_t} = \mu_t(\theta) + \varepsilon_t$$

where $\mu_t(\theta)$ is the conditional mean vector and

$$\varepsilon_t = \mathrm{H_t}^{1/2}(\theta)\mathrm{Z_t}$$

where $\mathrm{H_t}^{1/2}(\theta)$ is positive definitive matrix and $\mathrm{Z_t}$ is assumed to be a I.I.D. vector $\mathrm{N} \times 1$, with $E(Z_t)$=0 and $Var(Z_t) = \mathrm{I_N}$

Depending on the formulation of $\mathrm{H_t}$, several different multivariate GARCH models have been developed, such as the *VECH*, the diagonal *VECH* and the BEKK models. Bollerslev et al. (1986) proposed that $\mathrm{H_t}$ is a linear function of the lagged squared errors and cross products of errors and lagged values of the elements of $\mathrm{H_t}$ as follows.

$$\mathrm{vech}(H_t) = \mathrm{vech}(C) + \sum_{i=1}^{q} A_i\, \mathrm{vech}(\varepsilon_{t-i}\varepsilon_{t-i}') + \sum_{i=1}^{p} B_i\, \mathrm{vech}(H_{t-i})$$

where $\varepsilon_t = (\varepsilon_{1t}, \varepsilon_{2t} \dots\dots \varepsilon_{Nt})'$ are the error terms associated with the conditional mean equations for $r_{\ t} = (r_{\ 1t}, \dots\dots r_{\ Nt})$. C is an $(N \times N)$ positive definite matrix of parameters and A_i and B_i are $[N(N+1)/2 \times N(N+1)/2]$ matrices of parameters. Vech $(\cdot)$ operator takes the 'upper triangular' portion of a symmetric matrix, and stacks each element into a vector with a single column.

There are some problems with this model. Firstly, the number of the parameters to be estimated is very large. Even in the simple case of two series N=2 and p=1, q=1, 21 parameters need to be estimated in VECH model. Another limitation is the restrictions on the parameters are needed to ensure that the conditional variance matrix is positive definite (Li 2007). Hence Bollerslev, Engle and Wooldridge (1988) introduced the diagonal VECH model. This model assumes that A_i and B_i are diagonal matrices, which implies less parameters to be estimated (e.g. for N=2 and p=1, q=1, the number of parameters is equal to 9). But the positive definite of the conditional variance matrix is still not guaranteed. Meanwhile, the diagonal VECH model does not capture the volatility spillover effects between different markets since the diagonal elements A_i and B_i capture the markets' own ARCH and GARCH effects and the off-diagonal elements A_i and B_i indicates the cross-market volatility spillover effects. Thus we introduce the multivariate GARCH model in the style of BEKK proposed by Engle and Kroner (1995).The BEKK model improves on both VECH and diagonal VECH since the H matrix is always ensured to be positive definite. It is represented by

$$H_t = C'C + A_i'\varepsilon_{t-1}'\varepsilon_{t-1}A_i + B_i'H_{t-1}B_i$$

where C is $N \times N$ upper triangular matrix of constants, while A_i and B_i are $N \times N$ matrices of parameters. We focus on a GARCH (1,1) specification since it has been shown to be a parsimonious representation of conditional variance that can adequately fit many econometric time series (Tim, Robert et al. 1988)**.** In the case of two variables (N=2) and p=q=1, the above equation can be written out in the following.

$$\begin{bmatrix} h_{11,t} & h_{12,t} \\ h_{21,t} & h_{22,t} \end{bmatrix} = \begin{bmatrix} c_{11} & c_{12} \\ 0 & c_{22} \end{bmatrix}\begin{bmatrix} c_{11} & 0 \\ c_{12} & c_{22} \end{bmatrix} + \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}\begin{bmatrix} \varepsilon_{1,t-1}^2 & \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon_{1,t-1}\varepsilon_{2,t-1} & \varepsilon_{2,t-1}^2 \end{bmatrix}\begin{bmatrix} a_{11} & a_{21} \\ a_{12} & a_{22} \end{bmatrix}$$
$$+ \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}\begin{bmatrix} h_{11,t-1} & h_{12,t-1} \\ h_{21,t-1} & h_{22,t-1} \end{bmatrix}\begin{bmatrix} b_{11} & b_{21} \\ b_{12} & b_{22} \end{bmatrix}$$

The symmetric matrix A captures the ARCH effects, the elements a_{ij} of the symmetric matrix A measure the degree of innovation from market *i* to market *j*. While the matrix B focus on the

GARCH effects, the elements b_{ij} in matrix B represent the persistence in conditional volatility between market *i* and market *j (Worthington and Higgs 2004)*. In other words, the diagonal parameters in matrices A_i and $B_i - a_{11}$, a_{22} and b_{11} , b_{22} capture the effects of own past shocks and volatility on its current conditional variance. The off-diagonal parameters in matrices A_i and B_i , a_{ij} and b_{ij}, measure the cross-market influences on the conditional variances and covariances, which is also known as 'volatility spillover' effects.

3.6.2 Estimation for Multivariate GARCH (Brooks 2002)

Under the assumption of conditional normality, the parameters of the multivariate GARCH model can be estimated by maximizing the log likelihood function.

$$L(\vartheta) = -\frac{TN}{2}\log 2\pi - \frac{1}{2}\sum_{i=1}^{t}(\log|H_t| + \varepsilon_t^{'} H_t^{-1}\varepsilon_t)$$

where θ denotes all the unknown parameters to be estimated. N is the number of the series in the system and T is the number of the observations. This log likelihood function is maximized by using the BHHH (Berndt, Hall and Hausman) algorithm.

4. Data and preliminary Analysis

4.1 Data selection and design

The analysis in this paper uses the daily stock closing price P_t, which are measured by local currencies. The raw data include Shanghai Stock Exchange (A-share and B-share indices); Shenzhen Stock Exchange (A-share and B-share indices); Hang Seng index in Hong Kong and S&P 500 composite index in US. The Hang Seng index includes 45 large firms and represents almost 75% total capitalization of stock exchange in Hong Kong, and thus is regarded as the main indicator to capture the stock market performance in Hong Kong. All data are downloaded from Lund Financial DataStream, LINC. The reason we use the daily data is that the weekly or monthly data may be too long to capture the interactions that may last only a few days (Cheol and Sangdal 1989). For level series, the stock indices are transformed into natural logarithm form to smooth the financial series. For equity returns, the first differences of log stock indices are adopted.

$R_t=\ln(P_t / P_{t-1})*100$

Figure 1 illustrates the twelve-hour difference between China and the United States, We take some adjustments for the date of the data, i.e. the stock price in China at time *t* is corresponding to that of US at *t-1*.

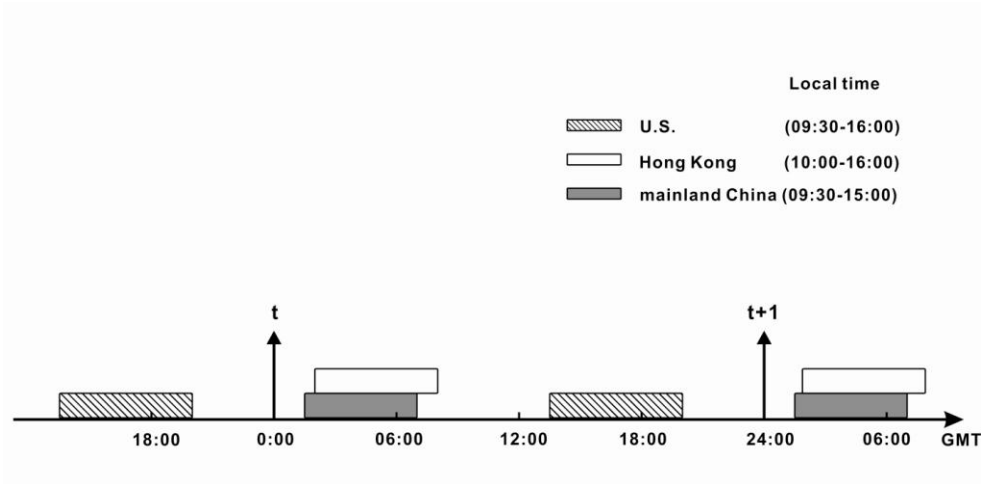

Figure 1. Time zone difference between China and US

The perspective of this paper is to investigate the dynamic linkages between China and US stock markets during two financial crises. The following stock markets in Table 1 are chosen according to its own features. Mainland China stock markets belong to the emerging equity market. Compared with mainland markets, Hong Kong stock market is relatively developed market. Finally, US stock market can be treated as the most developed stock market. This selection will indicate the dynamic linkages between China and US stock markets more clearly.

Table 1. Data selection and design

Location	Stock index	Short for	Transformation
Shanghai	Shanghai stock exchange A share index	SHA	Logarithm
	Shanghai stock exchange B share index	SHB	Logarithm
Shenzhen	Shenzhen stock exchange A share index	SZA	Logarithm
	Shenzhen stock exchange B share index	SZB	Logarithm
Hong Kong	Hang Seng index	HS	Logarithm
United States	S&P500	S&P500	Logarithm

Since the analysis mainly investigates the co-movements between China and US stock markets during the turbulent periods, two recent financial crises are considered. One is Asian Financial Crisis. Its sample period ranges from 1st July, 1996 to1st July, 1999; the alternative is Subprime Financial Crisis. Its sample period is from 1st February, 2007 to 1st February, 2010. Each period contains 784 observations. The selection of the two financial crises is to test whether there are spillover effects between different equity markets during chaotic periods. If the spillover effects exist, we will compare these two financial crises to exam how the spillover effects change with the development of the stock markets in China.

4.2 Preliminary analysis

Figure 1 and 2 in Appendix show the returns of share price indices in Asian Financial Crisis and Subprime Financial Crisis, respectively. The returns of different stock indices under two financial crises exhibit the feature of volatility clustering, i.e. large changes tend to follow large changes, and small changes tend to follow small changes, which is common in the financial data.

Summary statistics for the return series are presented in Table 2. Shenzhen A-share index has the highest mean during the two financial crises. The sample means are negative for S&P 500 and Hang Seng indices in the Subprime Financial Crisis. In the regards to the variance, mainland China and Hong Kong stock markets are more volatile than US. In addition, the Jarque-Bera statistics reject the null hypothesis that the returns are normally distributed for all indices since the probability of BJ test is equal to zero. The sign of the skewness vary with different indices. Moreover all return series are leptokurtic, which indicates all underlying data have fatter tails and higher peakness than normal distribution.

Table 2. Descriptive Statistics of Index Return

	Mean	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Probability
Panel A: Asian Financial Crisis						
SHA	0.042387	0.880270	-0.813907	8.338436	1017.523	0.000000
SHB	0.006443	1.137670	0.360334	6.748247	475.9114	0.000000
SZA	0.056065	1.002335	-0.932709	6.974700	629.7487	0.000000
SZB	0.022642	1.182062	0.148592	7.800022	755.5319	0.000000
HS	0.014072	0.982149	0.359066	12.50995	2971.190	0.000000
S&P500	0.040013	0.489627	-0.528327	7.990322	849.9810	0.000000
Panel B: Subprime Financial Crisis						
SHA	0.002787	0.990254	-0.354209	4.786012	120.4415	0.000000
SHB	0.021325	1.168484	-0.337026	5.578128	231.6730	0.000000
SZA	0.028692	1.065540	-0.626415	4.374877	112.8782	0.000000
SZB	0.013513	0.982510	-0.480126	5.588183	248.6277	0.000000
HS	-0.000431	1.018080	0.130188	7.968264	807.5158	0.000000
S&P500	-0.015419	0.807751	-0.168178	9.281911	1291.152	0.000000

5. Application and Empirical results

5.1 Unit root and stationary tests

Before investigating the linkages among different stock indices, the Augmented Dickey-Fuller (ADF) test and the Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) test are applied to examine the stationary properties of the level series and return series. The null hypothesis of ADF test is that the series has a unit root, whereas stationary is the null hypothesis in the KPSS test. Thus we perform KPSS test as confirmatory test of the results of ADF. But if two approaches are contradicted, KPSS is preferred.

As discussed in the methodology part, firstly we need to specify which estimation equation should be used when performing the unit root tests. The form of the estimation equation can be based on the plot of the data (Appendix A). All log price series (level series) do not start from the original point. Moreover they all exhibit upward or downward trends. Thus we test the unit root with drift and/or deterministic trend. But all return series (first log difference) do not exhibit the upward or downward trend, and they do have intercepts. Therefore, the form of the estimation equation only contains the constant term. Meanwhile, as mentioned before, the appropriate lag lengths are determined by the information criteria, such AIC and SBIC. If contradictive results are achieved, SBIC is preferred.

Table 3. Results of unit root and stationary tests

Panel A. Asian Financial Crisis				
Index	**ADF (constant)**	**KPSS (constant)**	**ADF (constant and trend)**	**KPSS (constant and trend)**
		Level series		
HS	-1.573	1.190**	-1.483	0.342**
SHA	-2.168	1.726**	-2.628	0.454**
SHB	-1.126	2.140**	-1.242	0.521**
SZA	-4.065**	0.687*	-3.923*	0.380**
SZB	-1.177	2.202**	-1.482	0.420**
S&P500	-0.691	3.322**	-3.238	0.295**
		Return series		
HS	-14.318**	0.166		
SHA	-28.076**	0.084		
SHB	-22.867**	0.246		
SZA	-27.163**	0.218		
SZB	-22.253**	0.212		
S&P500	-28.383**	0.032		

Panel B. Subprime Financial Crisis

Index	ADF (constant)	KPSS (constant)	ADF (constant and trend)	KPSS (constant and trend)
		Level series		
HS	-1.484	1.042**	-1.588	0.386**
SHA	-1.070	1.418**	-1.667	0.437**
SHB	-1.167	1.109**	-1.446	0.432**
SZA	-1.497	0.718*	-1.697	0.451**
SZB	-0.930	1.139**	-0.970	0.527**
S&P500	-1.111	2.397**	-1.088	0.395**
		Return series		
HS	-29.645**	0.139		
SHA	-28.544**	0.271		
SHB	-25.989**	0.242		
SZA	-26.295**	0.274		
SZB	-26.819**	0.286		
S&P500	-23.737**	0.175		

* (**) denotes rejection of the null hypothesis at the 5% (1%) significance level

The null hypothesis of ADF test is that a series does contain a unit root (non-stationary process) against the alternative of stationary.

The null hypothesis of KPSS test is that a series is stationary process against the alternative of non-stationary process.

Critical values for ADF tests (Constant)

1% level = -3.438508

5% level = -2.865030

Critical values for ADF tests (Constant+ trend)

1% level = -3.969860

5% level = -3.415588

Critical values for KPSS tests (Constant)

1% level = 0.739000

5% level = 0.463000

Critical values for KPSS tests (Constant+ trend)

1% level = 0.216000

5% level = 0.146000

Firstly, we analyze the results of ADF and KPSS tests under Asian Financial Crisis (See Panel A in Table 3). In terms of ADF test including constant term, for all level series except SZA, we cannot reject the null hypothesis of a unit root process. But for SZA series, the null hypothesis of a unit root is rejected at the 1% significance level. In terms of ADF test including constant and trend terms, for all level series, we cannot reject the null hypothesis of a unit root. In terms of KPSS tests including constant and/or trend terms, for all level series except SZA, we can reject the null hypothesis of stationary process at 1% significance level. The evidence is that when KPSS test including constant term is applied to SZA series, the null hypothesis of stationary process is rejected at 5% level. However, for all return series under ADF test including constant term, we can reject the null hypothesis of a unit root at the 1% level. For all return series under

KPSS test including constant term, we cannot reject the null hypothesis of stationary process at the 5% significant level.

Secondly, we analyze the findings of ADF and KPSS tests under Subprime Financial Crisis (see Panel B in Table 3). In terms of ADF tests including constant and/or trend terms, for all level series, we cannot reject the null hypothesis of a unit root process at the 5% significance level. In terms of KPSS tests including constant and/or trend terms, for all level series except SZA, we can reject the null hypothesis of stationary process at the 1% significance level. The evidence is that when KPSS test including constant term is applied to SZA series, the null hypothesis of stationary process is rejected at the 5% level. However, for all return series, we can reject the null hypothesis of a unit root process at the 1% level when ADF test including constant term is applied. And we cannot reject the null hypothesis of stationary process at the 5% significance level when KPSS test including constant term is used.

Our tests suggest that all level series have a unit root, and that all return series are stationary. In other words, all level series appear to be integrated of order one, I(1).

5.2 Cointegration between China's stock markets and US stock market: the Johansen Test

Don't put all eggs in one basket! This is a golden rule for risk management. However, in the real world, investors mainly invest in domestic market due to "Home Bias". "Home bias in equities says that domestic investors' holdings of foreign assets are too small relative to portfolio shares that would optimally hedge risk and possibly even increase returns" (Karen 1999). Theoretically, to diversify the investment risk, the investors should invest more than one national stock market and pay close attentions to the linkages among international equity markets.

With the development of China's economy, more and more investors are interested in the relationship between China's stock markets and international stock markets, especially, US stock market. If China's equity markets and US equity market are very strongly correlated, the diversification will be less effective than two segmented equity markets. To some extent, the cointegration captures the degree of diversification.

In the last section, several approaches have been used to test the stationarity of the log stock prices and log returns. Each level series (log stock prices) has a unit root, while each return series (log first difference of stock prices) is stationary. This section mainly employs the Johansen procedure to test the cointegration among the six stock indices.

5.2.1 Lag length selection in VAR models

Before running the Johansen test, the selection of lag length and the identification of deterministic components should be done first.

The choice of lag length mainly depends on the information criteria since there are so many restrictions on Likelihood ratio test. If two criteria show contradictable results, SBIC is more reliable. To investigate the relationship between two markets clearly, the stock indices are divided into two groups. One is Shanghai, Hong Kong and US stock markets. The alternative is Shenzhen, Hong Kong and US stock markets.

Table 4. The selection of lag length based on VAR models

Panel A. Asian Financial Crisis					
The First Group	**VAR(1)**	VAR(2)	VAR(3)	VAR(4)	VAR(5)
Log likelihood	8117.215	8142.448	8144.070	8152.171	8152.919
AIC	-20.68254	**-20.73260**	-20.72233	-20.72864	-20.71609
SBIC	**-20.56343**	-20.51799	-20.41202	-20.32245	-20.21382
The Second Group	**VAR(1)**	VAR(2)	VAR(3)	VAR(4)	VAR(5)
Log likelihood	8003.214	8031.048	8029.364	8043.511	8046.339
AIC	-20.39135	-20.44769	-20.42859	**-20.45003**	-20.44246
SBIC	**-20.27224**	-20.23308	-20.11828	-20.04383	-19.94019
Panel B. Subprime Financial Crisis					
The First Group	VAR(1)	**VAR(2)**	VAR(3)	VAR(4)	VAR(5)
Log likelihood	8022.948	8129.401	8150.527	8147.838	8146.016
AIC	-20.46790	-20.72574	**-20.76545**	-20.74413	-20.72498
SBIC	-20.34867	**-20.51091**	-20.45484	-20.33752	-20.22219
The Second Group	VAR(1)	**VAR(2)**	VAR(3)	VAR(4)	VAR(5)
Log likelihood	8129.666	8238.157	8267.171	8267.796	8262.899
AIC	-20.74083	-21.00424	**-21.06454**	-21.05211	-21.02545
SBIC	-20.62160	**-20.78942**	-20.75392	-20.64550	-20.52266

The results are presented in Table 4. For the first group under Asian Financial Crisis, AIC suggests VAR models with two lags, but SBIC selects only one lag. Thus, the optimal lag length for the first group is one based on SBIC. The remaining groups under the two financial crises follow the same rule that the results based on SBIC. Hence, the appropriate lag length is one for both groups under Asian Crisis and two lags under Subprime Crisis.

5.2.2 Deterministic components in the Johansen test—Pantula Principle

The results of estimating Models 2-4 are given in Table 5. Here, we employ the Pantula Principle and take the first group in Asian Financial Crisis as an example. Starting with the most restrictive model, the trace test statistic in Model 2 is 45.27157 which is less than its critical value 54.07904 at 5% level. Hence, the null hypothesis of no cointegration cannot be rejected. And this is the first

time that the null is not rejected. Thus, we would conclude that there is no cointegration vector. And Model 2 is suitable for the Johansen cointegration test.

Table 5. Pantula Principle

Panel A. Asian Financial Crisis						
	SHA, SHB, HS, S&P500			SZA, SZB, HS, S&P500		
NO. Cointegration	**Model 2**	Model 3	Model 4	**Model 2**	Model 3	Model 4
0	**45.27157**	37.00220	57.16969	**49.56844**	40.95142	58.91065
1	23.51870	15.37494	29.76052	25.93956	17.61259	32.99577
2	12.07018	7.409293	14.20474	12.55452	6.634965	12.57054
3	4.814112	0.480616	6.303723	4.805477	1.148730	3.789717
Panel B. Subprime Financial Crisis						
	SHA, SHB, HS, S&P500			SZA, SZB, HS, S&P500		
NO. Cointegration	**Model 2**	Model 3	Model 4	**Model 2**	Model 3	Model 4
0	**35.04476**	33.61989	45.08612	**45.88511**	44.04910	51.06896
1	20.26115	18.94118	23.66431	27.79124	26.19753	27.69565
2	9.503025	8.766332	10.86903	11.12097	9.537724	11.01285
3	1.075280	0.590105	2.646996	1.922788	1.922113	1.977262

In a word, there is no cointegration relationship among stock markets in the first crisis. Also, it is the same situation in the second financial crisis. Actually, the number of cointegration vectors has been known in this step. In the next step, the Johansen test just summaries the procedure above.

5.2.3 The Johansen approach

The results of Johansen cointegration test (Table 6) suggest that China's equity markets and US equity market are not cointegrated. It is good news for investors because they can hedge their investments or even gain substantial benefits by diversification. This results indicate that the lack of long-term integration between equity markets may be due to institutional idiosyncrasies, such as taxation structures, different investment cultures, home bias and macroeconomic policies between China and America (Clare Andrew, Maras et al. 1995). All these factors probably induce that equity markets operate largely independently of one another.

Table 6. The Johansen cointegration test

Panel A. Asian Financial Crisis						
	No. of	Lag	Trace	Critical	Max-eigen	Critical
SHA, SHB, HS, S&P500	0	1	45.27157	54.07904	21.75287	28.58808
SZA, SZB, HS, S&P500	0	1	49.56844	54.07904	23.62889	28.58808
Panel B. Subprime Financial Crisis						
	No. of	Lag	Trace	Critical	Max-eigen	Critical
SHA, SHB, HS, S&P500	0	2	35.04476	54.07904	14.78361	28.58808
SZA, SZB, HS, S&P500	0	2	45.88511	54.07904	18.09387	28.58808

5.3 Return spillover between China and US stock markets

In the long run, there is no cointegration between China and US stock markets even in turbulent periods. However, it may be possible that two variables are not cointegrated in the long run, but there might exist short run causal linkage. The short run interrelationships can be examined by the Granger Causality Analysis. This section concentrates on the return spillover between different stock markets during two chaotic periods.

5.3.1 Lag length selection according to information criteria

Since Pairwise Granger Causality tests are based on VAR models too, the number of lags in VAR model should be decided first. Table 7 represents the choice of lag lengths. During Asian Crisis, both information criteria select VAR(1) model for two groups. While AIC suggests VAR(2) model, SBIC suggests VAR(1) in Subprime Crisis. And the optimal lag length is still one since SBIC is preferred.

Table 7. Lag length in VAR models for different groups

Panel A. Asian Financial Crisis					
SHA, SHB, HS, S&P 500	VAR(1)	VAR(2)	VAR(3)	VAR(4)	VAR(5)
AIC	**9.441801**	9.455398	9.444698	9.469611	9.470417
SBIC	**9.560910**	9.670011	9.755005	9.875806	9.972693
SZA, SZB, HS, S&P 500	VAR(1)	VAR(2)	VAR(3)	VAR(4)	VAR(5)
AIC	**9.730457**	9.751710	9.728225	9.739883	9.750585
SBIC	**9.849566**	9.966322	10.03853	10.14608	10.25286
Panel B. Subprime Financial Crisis					
SHA, SHB, HS, S&P 500	VAR(1)	VAR(2)	VAR(3)	VAR(4)	VAR(5)
AIC	9.446473	**9.414567**	9.423680	9.441081	9.466872
SBIC	**9.565702**	9.629395	9.734299	9.847685	9.969655
SZA, SZB, HS, S&P 500	VAR(1)	VAR(2)	VAR(3)	VAR(4)	VAR(5)
AIC	9.177501	**9.141658**	9.131703	9.158894	9.174079
SBIC	**9.296730**	9.356486	9.442323	9.565498	9.676861

5.3.2 Stock return spillover effect: Pairwise Granger Causality tests

Table 8 reports the results of Granger causality tests among different stock markets during the two financial crises. During Asian Crisis, return of Hang Seng index Granger causes returns of all stock markets, except SZA. Correspondingly, returns of SHA and S&P500 also Granger cause Hang Seng (HS) index. There are no other Granger causality relationships. The following reasons may explain above results.

Firstly, the reasons that there are return spillover effects from Hong Kong to mainland, except Shenzhen A-share market are the maturity of Hong Kong stock market and close relationships between Hong Kong and mainland China. On the one hand, while stock markets in mainland were just at the beginning stage during Asian Crisis, Hong Kong stock market was relatively more mature than mainland. Meanwhile, Hong Kong played a key role as a financial hub in the Asian area. On the other hand, because of the geographic and economic ties between mainland and Hong Kong, the information was released easily and quickly from the maturity market - Hong Kong to the developing market – mainland China. Secondly, it is not surprising that bidirectional return spillovers between Hong Kong and US are found. On the one hand, Hong Kong, as one of the Asian financial centers, has more links with the global financial center - the United States. On the other hand, Hong Kong dollar was pegged to the US dollar during Asian Crisis. Finally, because of the immature and segmented stock markets and the information asymmetry problems in mainland, few foreign investors took a risk to invest equities in mainland. Hence, there is no Granger causality between mainland China and US.

Compared with Asian Crisis, one obvious finding during Subprime Crisis is that there are more unidirectional return causalities from mainland China to Hong Kong and the United States. One exception of these results is that Shenzhen A-share stock market only Granger causes Hang Seng stock market. Besides, there is a unidirectional return spillover from Hong Kong and the United States.

Several possible reasons could explain the results above. Firstly, with the rapid development of economy, China, as the largest emerging market, plays more important role in international financial markets. Secondly, according to the rules of the World Trade Organization (WTO), Chinese government should further open its domestic financial markets to foreign investors. Thus the liberalization of the capital markets not only reduces the transaction cost, but also attracts more foreign capital inflows. And sufficient capitals are the necessary condition of the economic growth. Thirdly, China had more international trade activities with the United States since joining WTO. The frequent communications and corporations mitigate information asymmetry problems, which makes the foreign investors know more about mainland China. Therefore, the bridge between stock markets in these two countries has been built.

Table 8. Granger causality test

Panel A. Asian Financial Crisis			
Null Hypothesis:	F-Statistic	Prob.	Conclusion
SP500 does not Granger Cause SHA	0.09495	0.7581	
SHA does not Granger Cause SP500	1.72936	0.1889	
HS does not Granger Cause SHA	4.07570	**0.0438**	HS→SHA
SHA does not Granger Cause HS	4.33514	**0.0377**	SHA→HS
SP500 does not Granger Cause SHB	0.00376	0.9511	
SHB does not Granger Cause SP500	0.03461	0.8525	
HS does not Granger Cause SHB	9.61994	**0.0020**	HS→SHB
SHB does not Granger Cause HS	0.04961	0.8238	
SP500 does not Granger Cause SZA	0.42694	0.5137	
SZA does not Granger Cause SP500	1.22345	0.2690	
HS does not Granger Cause SZA	1.17127	0.2795	
SZA does not Granger Cause HS	2.89873	0.0890	
SP500 does not Granger Cause SZB	0.06576	0.7977	
SZB does not Granger Cause SP500	0.20006	0.6548	
HS does not Granger Cause SZB	3.95447	**0.0471**	HS→SZB
SZB does not Granger Cause HS	0.02065	0.8858	
HS does not Granger Cause SP500	22.1482	**3.E-06**	HS→SP500
SP500 does not Granger Cause HS	5.67729	**0.0174**	SP500→HS
Panel B. Subprime Financial Crisis			
Null Hypothesis:	F-Statistic	Prob.	Conclusion
HS does not Granger Cause SHA	0.39959	0.5275	
SHA does not Granger Cause HS	10.3515	**0.0013**	SHA→HS
SP500 does not Granger Cause SHA	0.25151	0.6162	
SHA does not Granger Cause SP500	4.38734	**0.0365**	SHA→SP500
HS does not Granger Cause SHB	0.18820	0.6645	
SHB does not Granger Cause HS	11.5343	**0.0007**	SHB→HS
SP500 does not Granger Cause SHB	0.00220	0.9626	
SHB does not Granger Cause SP500	3.76429	**0.0527**	SHB→SP500
HS does not Granger Cause SZA	0.20490	0.6509	
SZA does not Granger Cause HS	11.9527	**0.0006**	SZA→HS
SP500 does not Granger Cause SZA	0.00324	0.9546	
SZA does not Granger Cause SP500	2.24130	0.1348	
HS does not Granger Cause SZB	1.12633	0.2889	
SZB does not Granger Cause HS	13.5940	**0.0002**	SZB→HS
SP500 does not Granger Cause SZB	0.49576	0.4816	
SZB does not Granger Cause SP500	5.53721	**0.0189**	SZB→SP500
SP500 does not Granger Cause HS	1.65551	0.1986	
HS does not Granger Cause SP500	108.073	**9.E-24**	HS→SP500

5.4 Impulse responses analysis

Although Granger Causality test shows the source of return spillovers among different stock markets, it doesn't reveal the sign of the relationship or how long these spillover effects would last. So impulse responses would give us more details about return spillover.

Figure 2 and 3 illustrate the generalized impulse response functions: 10-period responses of one variable to one unit of innovations of another variable. Based on the previous analysis, we only report the figures of impulse response for significant results in Granger causality tests.

During Asian Crisis, responses of three stock markets in mainland (i.e. SHA, SHB and SZA) to the shocks coming from Hong Kong are positive. The response of Shanghai B-share market to shocks from Hong Kong is much stronger than the responses of Shanghai A-share and Shenzhen A-share markets. Moreover, this response dies out after five periods, suggesting that the persistence of return spillover from Hong Kong to Shanghai B-market is longer than others. In addition, while the response of US to shocks coming from Hong Kong is positive, the response of Hong Kong to US's shocks is negative. And the return spillover effect from US to Hong Kong is much stronger than the effect from Hong Kong to US. The interesting finding is that response of Hong Kong to shocks from US and Shanghai A-share market is negative. The possible explanation is that due to its maturity and geographical location with Thailand, the Hong Kong stock market suffered serious hits during Asian Crisis. Numerous speculators got profit by short selling, leading to a downward pressure on the stock market. Thus the response of Hong Kong to the shock from abroad is negative.

The impulse responses under Subprime Crisis are more concentrated. Mainly, responses of both US and Hong Kong to shocks from mainland markets are positive. Moreover, response of Hong Kong to the shocks from mainland is much stronger than response of US to the shocks from mainland. However, the persistence of return spillovers from China mainland to US is longer.

Generally, variance decomposition generally offers similar information with impulse response, but it is often applied for forecasting. Thus, we only show the results of variance decomposition in Appendix B and do not discuss here.

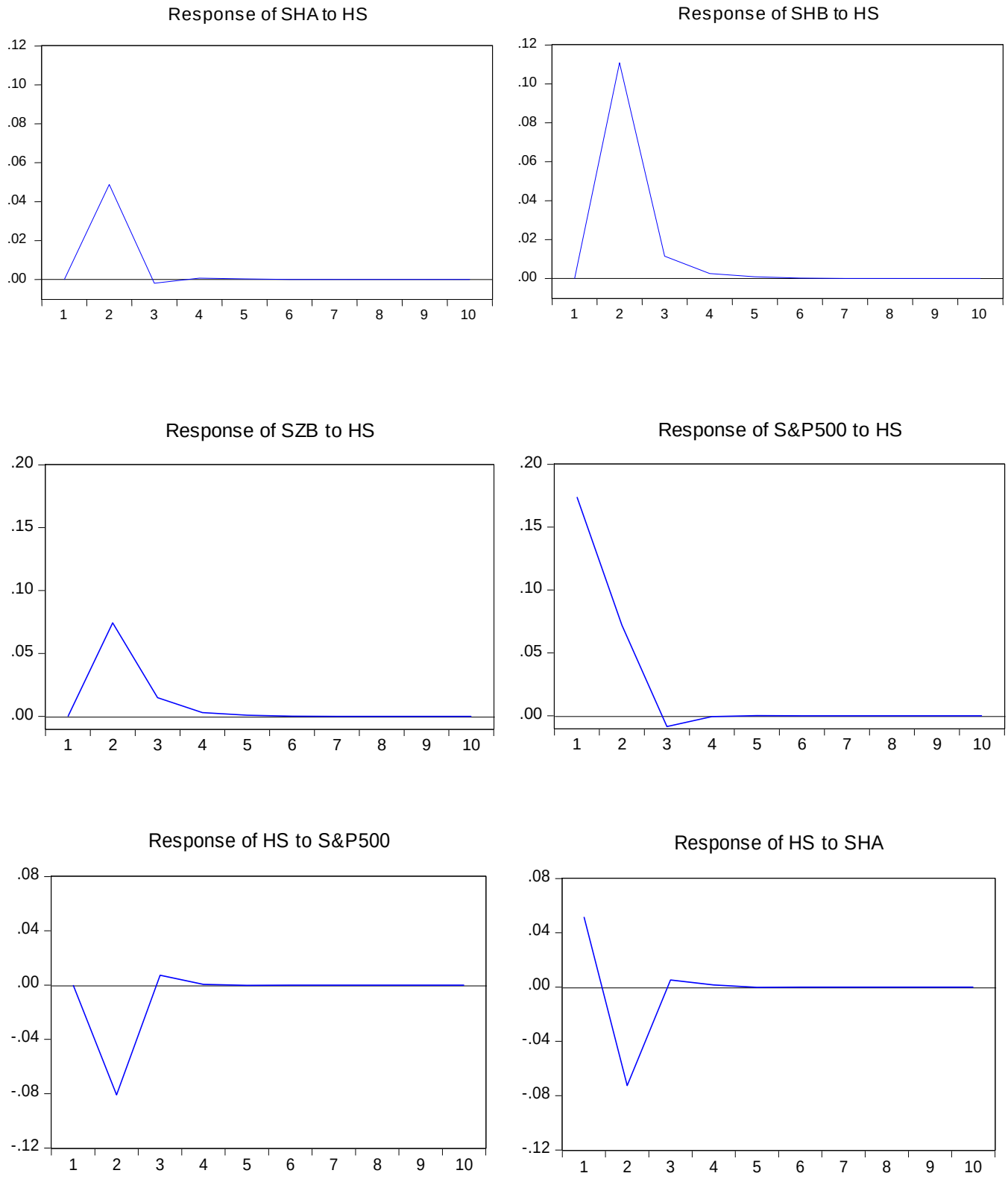

Figure 2. Impulse Responses under Asian Financial Crisis

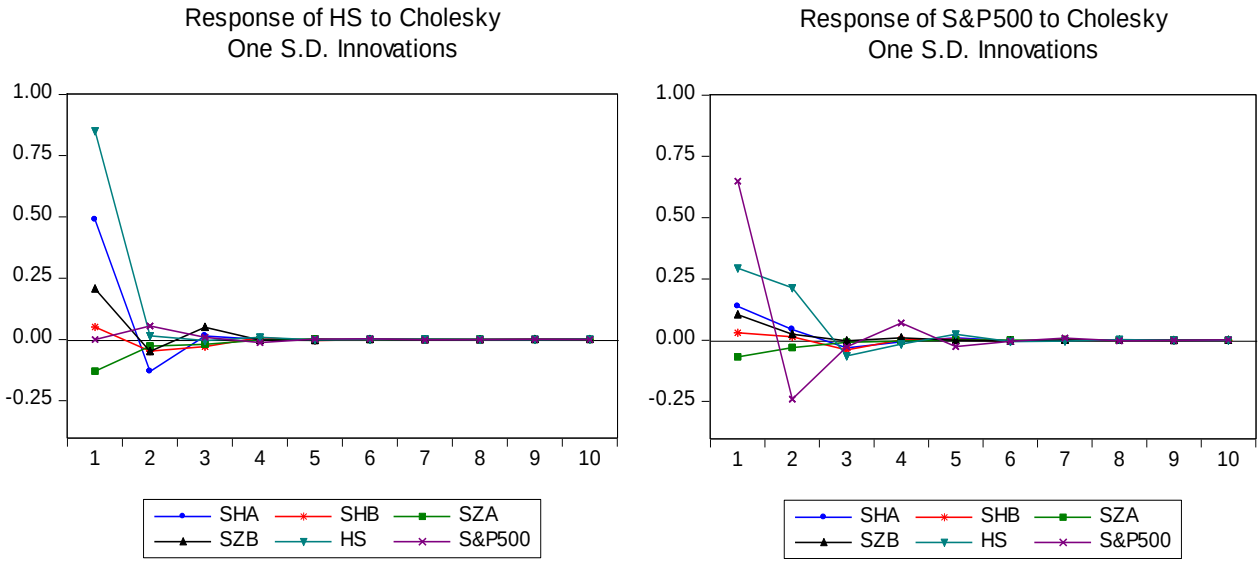

Figure 3. Impulse Responses under Subprime Financial Crisis

5.5 Multivariate GARCH-BEKK model

This paper applies trivariate GARCH-BEKK model to effectively capture the own and cross volatility spillovers between stock markets in China and United States. And the estimated results for the variance-covariance parameters are presented in Table 9 and 10.

It should be noted that six stock indices (i.e. S&P500, HS, SHA, SZA, SHB and SZB) are divided into four groups. In table 9 and 10, the stock exchanges in United States and Hong Kong are indexed as 1 and 3, respectively. Index 2 stands for four different stock exchanges in mainland China (i.e. SHA, SZA, SHB and SZB) depending on different groups. Due to the different inputs for four groups, we always get the different coefficient estimates for the same estimated parameters. For instance, A(1,1) in four groups give us different estimation results of own volatility effects of US stock markets.

5.5.1 Volatility spillover analysis in Asian Financial Crisis

Table 9 reports the estimated coefficients in the variance-covariance matrix of trivariate GARCH- BEKK model during Asian Financial Crisis.

Firstly, the own-volatility spillover effects, namely, A(1,1), A(2,2), A(3,3), in all markets are large and significant. The US stock market's own-volatility spillover effects range from 0.10 (group3) to 0.23 (group1). China mainland stock markets almost have 0.47 own-volatility effect except the Shenzhen "B" shares 0.64. And the own-volatility spillover in Hong Kong ranges from 0.37 (group1) to 0.40 (group2). On average, the own-volatility spillover effects are higher for the mainland stock markets than for the US and Hong Kong markets, this results indicate that the past own-volatility effects are stronger for the emerging markets than for the developed markets. Accordingly, the immaturity of the mainland stock markets accompany more volatility, which is consistent to the arguments that open economies have significantly lower volatilities (Bekaert and Harvey Campbell 1997).

Secondly, in terms of cross-volatility effects among different stock markets, the volatility spillovers between US and Hong Kong are significant. The sign of volatility spillover from US to Hong Kong is negative, but the volatility spillover from Hong Kong to US is positive. For mainland China, past innovation in US only has a negative effect on current volatility in Shenzhen B share market. There are no other spillover effects between mainland China and US. Shenzhen is the earliest and most important "special economic zones" which attracts foreign capital inflows. And most companies listed on SZSE are export-oriented firms and they are less monitored by the Chinese government. All the features supply a sound environment for the foreign investors. Compared own-volatility with cross-volatility in Hong Kong, past volatility shock in Hong Kong has a greater effect on its own current volatility than past volatility shocks in US.

Finally, consider the GRACH set of parameters, the diagonal values in B matrix indicates the persistence of own stock markets' volatility. The own volatility persistence in all markets are significant and close to one. That means shocks in volatility don't vanish quickly over time (Fernandez-Izquierdo and Lafuente Juan 2004). For the cross-volatility persistence, the more influential market would be the United States. The cross-volatility persistence from US to Hong Kong varies from -0.7613 to 0.0635. Inversely, the cross-volatility persistence from Hong Kong to US ranges from -0.0230 to 0.1995. That means the past volatility shocks in US have a larger effect on Hong Kong current volatility over time than the opposite cross- volatility persistence. This would point out that US stock market is the most developed financial market and has significant effects on the relative developed stock market in Hong Kong. As a result of relatively closed nature of financial system in China, neither Hong Kong nor US stock market has a cross-volatility persistence effect on mainland stock markets.

5.5.2 Volatility spillover analysis in Subprime Financial Crisis

The empirical findings under Subprime Financial Crisis have great differences from the outcomes during Asian Financial Crisis. Table 10 presents the estimated coefficients for the variance-covariance matrix under Subprime Financial Crisis.

Firstly, US own-volatility effect is only significant in Group1 (0.1050). But the own-volatility effects of other stock markets are significant for four groups. Compared with that in Asian Crisis, US and Hong Kong markets' own-volatility effects have reduced to 50 percent. For mainland China, the own-volatility also decreases. Especially, the own-volatility of Shenzhen B-market decreases from 0.6371 (Asian Crisis) to 0.1780 (Subprime Crisis). This indicates that after suffering from Asian Financial Crisis, both China and the United States began to reform their financial systems to defend overseas shocks. With the development of financial globalization, the stock markets in mainland China become more and more mature. Previous volatility shocks in individual mainland market have a greater effect on current volatility than past volatility effects from developed markets on mainland market current volatility.

Secondly, the most remarkable finding in Table 10 is that there are more significant volatility transmissions (a_{ij}) between different stock markets during Subprime Financial Crisis. Like the outcomes in previous crisis, there still exist significant and asymmetric volatility spillover effects between Hong Kong and US. Besides the links between US and Hong Kong, past shocks in US have a positive effect on current volatility in Shanghai A-share market, Shenzhen B-share market, but a negative effect on Shanghai B-share market and Shenzhen A-share market. Correspondingly, the stock markets in mainland have feedback effects on current volatility in US except Shenzhen B-share market. There is a unidirectional volatility spillover from Hong Kong to mainland stock markets. Moreover, past shocks in Hong Kong influence more on current volatility in A-share markets than that in B-share markets since as the squared values of parameters A(3,2) in group 1 and 2 are larger than A(3,2) in group 3 and 4. Compared own-

volatility with cross-volatility in Shanghai, past volatility shocks in Shanghai markets (both "A" share and "B" share) are more powerful on its own current volatility than volatility transmission from US But for the Shenzhen stock markets (both "A" share and "B" share), we find the current volatility in Shenzhen is effected more by the volatility transmission from US than by its own past volatility.

Finally, in the GRACH set of parameters, the own volatility persistence in all markets are also significantly close to one. Volatility is stationary over time. Similarly, the asymmetric cross-volatility persistence exists between US and Hong Kong. However, the volatility persistence from US to Hong Kong is greater than the opposite direction. In the case of US and mainland China relationship, previous shocks in US have a larger effect on current volatility in mainland stock markets over time than the opposite cross-volatility persistence except Shenzhen B-share market. There is no feedback from Shenzhen B-share market to US as the matching off-diagonal parameter B(2,1) in group 4 is insignificant. In terms of the volatility transmission between Hong Kong and mainland China, there is a bidirectional volatility spillover from Hong Kong to Shanghai A-share market, but an unidirectional volatility spillover from Hong Kong to Shenzhen A-share market. The evidence is that the off-diagonal parameters B(2,3) (group 1) and B(3,2) (group 1 and 2) are significant, while B(2,3) (group 2) is insignificant. In addition, other stock markets in mainland China have no cross-volatility persistence with Hong Kong.

5.5.3 Further discussions about volatility spillover effects

During Asian Financial Crisis, the degree of openness of mainland China and Hong Kong stock markets is not homogeneous. Mainland stock markets have imposed restricted controls. For instance, the domestic investors were not allowed to invest B-share markets and the foreign investors were only allowed to invest the B-share markets. Therefore the stock markets in mainland China are relatively segmented and undeveloped. However, Hong Kong, as an international financial center, has a sophisticated trading system and transparent disclosure of accounting information (Zhang, Zhao et al. 2009), which mitigate the information asymmetry problems for foreign investors. Thus, only volatility spillover effects between US and Hong Kong are significant. There is no volatility transmission among mainland China stock markets and US and Hong Kong.

After Hong Kong returned to mainland China on 1 July 1997, the stock market in Hong Kong was integrated more with mainland since the communications between them became more frequent. With mainland China joining the World Trade Organization (WTO) and the development of globalization, the economic growth in mainland China increased dramatically. Meanwhile, the financial system deregulation and liberalization in mainland China attracted more foreign capital inflows. In addition, the bilateral trade between mainland China and US are more frequently of international trade transactions between China and US. And more and more foreign

investors know about the largest emerging stock market - China. Therefore, as we expected, much more volatility spillover effects are presented during Subprime Crisis.

Overall, mainland China stock markets were relatively segmented during Asian Crisis. But during Subprime Crisis, although they seem not fully integrated with world economy, mainland China still became more integrated. Therefore, mainland stock markets were almost escaped from the 1997 Asian Crisis. Although stock markets in mainland China were not immunized against Subprime Crisis, they still did not suffer a lot. The following reasons can explain why mainland China did not suffer a lot during the two financial crises.

Firstly, Chinese government has imposed on strict restrictions on the movements of capital inflows and outflows except the payments of exports and imports. The inflows control can reduce the crisis risk by preventing banks and financial institutions from becoming excessively dependent on short-term foreign debt (Eichengreen 2003). The restrictions on capital outflows can prevent capital from flying out of the domestic country once crisis happens.

Secondly, a vital part of economic reform in mainland China has been the promoted foreign direct investment (FDI) inflows. Currently, the mainland is the largest FDI destination among the developing countries. Unlike foreign portfolio management which is the short-term investment, the FDI is the long-term participation. And Berument and Dincer (2004) have suggested that policymakers should be cautious to open their equity markets to the foreign investors. Furthermore, authorities should encourage foreign direct investment (FDI) relative to foreign portfolio management since the FDI is less volatile and more stable than foreign portfolio management. Consistent with the arguments of Berument and Dincer, the authority of mainland China has been always cautious to open their financial markets. The evidence is that despite the fact that the Chinese government has gradually loosen the restrictions imposed on the foreign investors by introducing the Qualified Institutional Investor (QFII) program, the mainland stock markets are still only open to a minority part of foreign investors.

Thirdly, the highly centralized financial systems to some extent stabilized the equity markets in the mainland, especially during and after the crisis. Unlike the non-centralized economy, the authority in mainland China fully supports the state-run banks and firms once crisis happens (Lin and Swanson 2008). In addition, China has enough foreign currency reserve to stable the domestic financial system and copes with various crises.

Now, we explain why mainland China was influenced more by Subprime Crisis. Firstly, as the US Subprime Crisis was spread to a global crisis. The domestic investors in mainland became panic and finally lost confidence about the equity markets. Meanwhile, the foreign institutional investors sold millions of dollars shares in China to cover the losses accrued in their home markets. Secondly, export incomes accounts for a significant portion of economy in mainland China. After global crisis happened, the unemployment rate increased and consumer spending

demands declined dramatically in US and other developed economies. Therefore, a large number of exports-dependent firms collapsed (Sharma Shalendra 2009).

Table 9. Estimated coefficients for the variance – covariance matrix of Trivariate BEKK model (Asian Financial Crisis)

Asian Financial Crisis		Group 1 (1=RS&P500, 2= RSHA, 3= RHS)		Group 2 (1=RS&P500, 2= RSZA, 3= RHS)		Group 3 (1=RS&P500, 2=RSHB, 3= RHS)		Group 4 (1=RS&P500, 2=RSHB, 3= RHS)	
Parameters		**Coefficient**	**Std error**	**Coefficient**	**Std error**	**Coefficient**	**Std error**	**Coefficient**	**Std error**
1	Mean(1)	0.0397***	0.0138	0.0426***	0.0157	0.0450***	0.0144	0.0503***	0.0151
2	Mean(2)	0.0260	0.0213	0.0312	0.0254	-0.0210	0.0261	-0.0265	0.0303
3	Mean(3)	0.0477	0.0201	0.0643***	0.0221	0.0563	0.0220	0.0688***	0.0238
4	C(1,1)	0.0748***	0.0207	0.0770***	0.0232	0.0856***	0.0217	0.0700***	0.0225
5	C(2,1)	0.0311	0.3220	0.0414	0.0681	0.1167	0.1020	0.0789	0.1757
6	C(2,2)	0.2508***	0.0494	0.3199***	0.0300	-0.2780***	0.0754	0.4683***	0.0501
7	C(3,1)	0.1092***	0.0228	0.0196	0.0537	0.0057	0.0425	0.0294	0.0449
8	C(3,2)	0.0059	0.1022	0.0048	0.0220	0.0537	0.0343	-0.0287	0.0293
9	C(3,3)	0.0000	0.1242	0.0603**	0.0306	0.0559	0.0351	0.0619**	0.0274
10	A(1,1)	0.2275***	0.0362	0.1149***	0.0307	0.1018***	0.0392	0.1069***	0.0333
11	A(1,2)	-0.0307	0.0481	-0.0107	0.0580	-0.1983	0.1618	-0.3599***	0.1061
12	A(1,3)	-0.2676***	0.0506	-0.3662***	0.0513	-0.3654***	0.0580	-0.3561***	0.0516
13	A(2,1)	0.0091	0.0137	-0.0195	0.0137	0.0076	0.0131	0.0142	0.0141
14	A(2,2)	0.4714***	0.0407	0.4701***	0.0413	0.4740***	0.0438	0.6371***	0.0508
15	A(2,3)	0.0331	0.0200	0.0033	0.0184	-0.0045	0.0286	0.0186	0.0244
16	A(3,1)	-0.0160	0.0156	0.0837***	0.0147	0.0986***	0.0209	0.0931***	0.0144
17	A(3,2)	-0.0159	0.0208	0.0098	0.0225	0.0648	0.0878	0.0277	0.0377
18	A(3,3)	0.3664***	0.0317	0.3994***	0.0314	0.3878***	0.0404	0.3823***	0.0284
19	B(1,1)	-1.0372***	0.0177	0.9761***	0.0133	0.9701***	0.0136	0.9778***	0.0119
20	B(1,2)	-0.0331	0.1469	-0.0030	0.0275	0.0004	0.0552	0.0567	0.0634
21	B(1,3)	-0.7613***	0.1514	0.0695	0.0288	0.0706***	0.0269	0.0635***	0.0238

22	B(2,1)	0.0169	0.0395	0.0091	0.0082	-0.0112	0.0086	-0.0166	0.0124
23	B(2,2)	0.8474***	0.0222	0.8256***	0.0264	0.8473***	0.0422	0.6729***	0.0418
24	B(2,3)	-0.0117	0.0191	-0.0005	0.0126	0.0175	0.0207	-0.0075	0.0250
25	B(3,1)	0.1995***	0.0490	-0.0246***	0.0053	-0.0230***	0.0076	-0.0251***	0.0050
26	B(3,2)	0.0075	0.0170	0.0016	0.0087	-0.0057	0.0320	0.0156	0.0220
27	B(3,3)	1.0096***	0.0174	0.9189***	0.0118	0.9175***	0.0180	0.9244***	0.0105

Note: ***, **and* represent the levels of significance of 1%, 5% and 10% respectively.

Table 10.Estimated coefficients for the variance – covariance matrix of Trivariate BEKK model (Subprime Financial Crisis)

Subprime Financial Crisis		Group 1 (1=RS&P500, 2= RSHA, 3= RHS)		Group 2 (1=RS&P500, 2= RSZA, 3= RHS)		Group 3 (1=RS&P500, 2= RSHB, 3= RHS)		Group 4 (1=RS&P500, 2= RSZB, 3= RHS)	
Parameters		**Coefficient**	**Std error**	**Coefficient**	**Std error**	**Coefficient**	**Std error**	**Coefficient**	**Std error**
1	Mean(1)	0.0314*	0.0187	0.0098	0.0157	0.0061	0.0167	0.0392**	0.0182
2	Mean(2)	0.0136	0.0318	0.0641*	0.0344	0.0498	0.0335	0.0434	0.0313
3	Mean(3)	0.0201	0.0227	0.0404*	0.0231	0.0398	0.0257	0.0353	0.0231
4	C(1,1)	-0.0073	0.0264	0.0832***	0.0262	0.1098***	0.0273	-0.0168	0.0267
5	C(2,1)	0.2097***	0.0489	-0.0062	0.1098	-0.0020	0.0582	0.1816	0.2671
6	C(2,2)	0.0105	0.0730	0.3930***	0.0575	0.2791***	0.0338	0.1838	0.2488
7	C(3,1)	0.1869***	0.0291	0.1629***	0.0406	0.1773***	0.0423	0.1401*	0.0796
8	C(3,2)	0.0091	0.0605	0.0807**	0.0355	0.0594*	0.0320	-0.0525	0.2167
9	C(3,3)	0.0000	0.1139	0.0000	0.0663	0.0000	0.0905	0.0038	0.2470
10	A(1,1)	0.1050**	0.0542	-0.0381	0.0499	-0.0554	0.0461	0.0639	0.0567
11	A(1,2)	0.1013***	0.0334	-0.3875***	0.0693	-0.2983***	0.0654	0.2295***	0.0433
12	A(1,3)	0.4081***	0.0413	-0.6241***	0.0511	-0.5988***	0.0538	0.4153***	0.0417
13	A(2,1)	0.0511***	0.0194	-0.0863***	0.0166	-0.0299**	0.0142	0.0029	0.0180
14	A(2,2)	-0.1658***	0.0336	0.3354***	0.0508	0.3574***	0.0296	0.1780***	0.0392
15	A(2,3)	-0.0039	0.0256	-0.0135	0.0268	0.0267	0.0179	-0.0007	0.0249
16	A(3,1)	-0.2067***	0.0370	0.1894***	0.0246	0.1770***	0.0238	-0.1777***	0.0366
17	A(3,2)	0.1326***	0.0339	0.1465***	0.0463	0.0981**	0.0388	-0.0967**	0.0431
18	A(3,3)	0.1497***	0.0384	0.2042***	0.0501	0.1881***	0.0462	0.1140***	0.0401
19	B(1,1)	0.7937***	0.0352	1.0185***	0.0122	1.0206***	0.0129	0.8048***	0.0279
20	B(1,2)	-0.0870***	0.0280	0.0549**	0.0218	0.0549**	0.0239	-0.1095***	0.0278
21	B(1,3)	-0.2270***	0.0449	0.2201***	0.0274	0.2128***	0.0358	-0.2242***	0.0366
22	B(2,1)	-0.0335***	0.0102	0.0436***	0.0129	0.0217***	0.0078	-0.0102	0.0129

23	B(2,2)	0.9502***	0.0173	0.8451***	0.0435	0.8913***	0.0179	0.9384***	0.0236
24	B(2,3)	-0.0451***	0.0170	0.0119	0.0220	-0.0028	0.0114	-0.0042	0.0234
25	B(3,1)	0.2288***	0.0316	-0.1192***	0.0183	-0.1226***	0.0213	0.2132***	0.0249
26	B(3,2)	0.0425*	0.0238	-0.0489***	0.0289	-0.0224	0.0274	0.0280	0.0232
27	B(3,3)	0.9914***	0.0253	0.8129***	0.0227	0.8264***	0.0268	0.9867***	0.0278

Note: ***, **and* represent the levels of significance of 1%, 5% and 10% respectively.

6. Conclusion and Further Studies

With the development of electronic communication and financial liberalization, the stock markets linkages between developed and emerging economies are more apparent than before. Meanwhile, the events of financial crises have frequently happened and none of the economies can be completely insulated. This paper explores the short-run and long-run dynamic linkages between China (mainland and Hong Kong) and US stock markets during Asian Crisis and Subprime Crisis. Furthermore, this study not only examines the return causality relationships, but also volatility spillover effects. Firstly, long run relationship between different markets' indices has been investigated by applying the Johansen cointegration test. Further, Granger causality tests are implemented to examine the return spillover effects among different equity markets. Then, more information about Granger causality will be given by generalized impulse response analyses. Finally, the multivariate GARCH – BEKK model is built to capture the volatility spillover effects between returns of different stock indices. The above analyses use the daily closing stock price, which is measured by local currency, for instance, Chinese Yuan, Hong Kong dollar and US dollar. As a result of different time zones between China and US, we take some adjustments for the date of the data, i.e. the stock price in China at time t is corresponding to that of US at $t-1$.

The results of the Johansen cointegration test show that there are no long run relationships on stock indices between China and US. The weak market linkage in the long term provides investors potential gains from international diversifications. However, in terms of the return spillover effects, Hong Kong market Granger causes other markets except Shenzhen A-share market under Asian Crisis. Correspondingly, Shanghai A-share and US stock markets have feedback effects on Hong Kong. This outcome illustrates the Hong Kong stock market plays an important role in Asian Crisis. However, during Subprime Crisis, more unidirectional return causalities are found from mainland China to Hong Kong and US, which suggests that mainland China as the largest emerging market plays more role in international financial markets. Volatility spillover effects are analyzed through trivariate GARCH-BEKK model. The results as we found are different from the case of return spillover. During Asian Crisis, the volatility spillovers between US and Hong Kong are significant. But the influence of US market is more powerful than Hong Kong. For mainland China, past innovation in US only has a negative effect on current volatility in Shenzhen B-share market. There are no other spillover effects between

mainland China and US. During Subprime Crisis, there are still significant and asymmetric volatility spillover effects between US and Hong Kong. And in the relationship between mainland China and US, US market positively affects Shanghai B-share and Shenzhen A-share markets, but negatively affects Shanghai B-share and Shenzhen A-share market. Likewise, all mainland stock markets have feedback effects on current volatility in US, except Shenzhen B-share market. In addition, there is a unidirectional volatility spillover from Hong Kong to mainland stock markets.

In summary, although the financial markets in mainland China have gradually opened and liberalized, the mainland stock indices are not cointegrated with US and Hong Kong in the long run. However, in the short run, the spillover effects on return and volatility exist between different groups of equity markets. Compared with Asian Crisis, the dynamic interactions between China and US have increased during Subprime Crisis. The findings in this paper have the following implications. First of all, the government of China should pay more attention to the spillover effects during chaos periods. The policy makers could adopt foreign capital inflow controls and encourage foreign direct investment (FDI) rather than equity investments. Secondly, the Chinese authority needs to keep enough foreign reserve to defend the financial shocks from foreign countries. Finally, both private and institutional investors should adjust their trading strategies and asset allocation decisions according to the spillover effects since they probably have chance to hedge their investments and get profits by investing into multinational equity markets, even during the turmoil periods.

However, this paper could also be improved in the following ways. Firstly, besides the US and Hong Kong stock markets, Japan stock markets could be included as a local factor to examine the integration of international financial markets. Secondly, the sample periods can be divided into three sub-samples: pre-crisis, during crisis and post-crisis. The comparisons between different sub-samples could probably supply more interesting findings. Finally, other multivariate GARCH models, such as the AR(1)-MGARCH model, could be applied to examine both return and volatility spillover effects.

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8. Appendix

Appendix A:

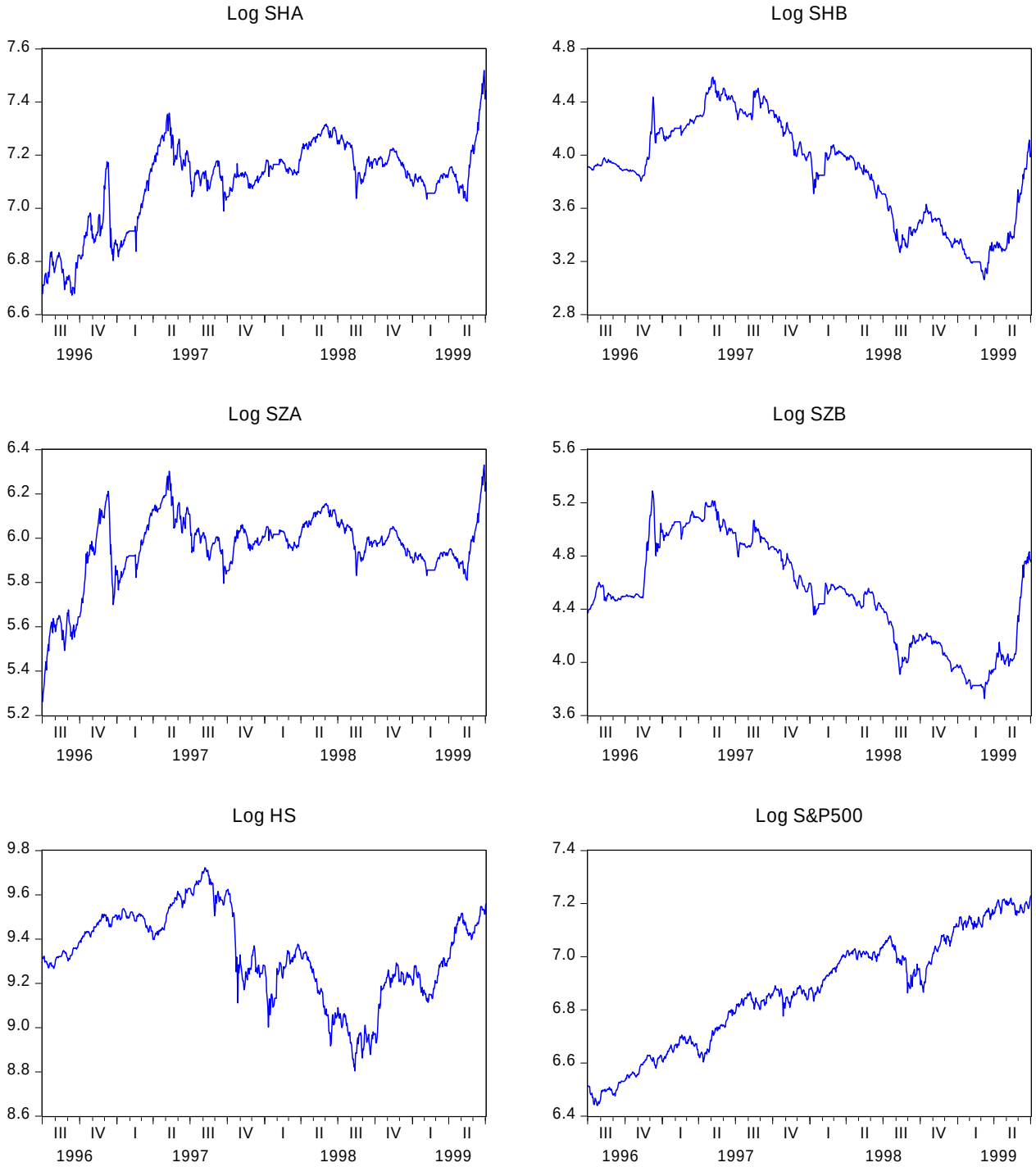

Figure 4. Log stock price indices during Asian Financial Crisis

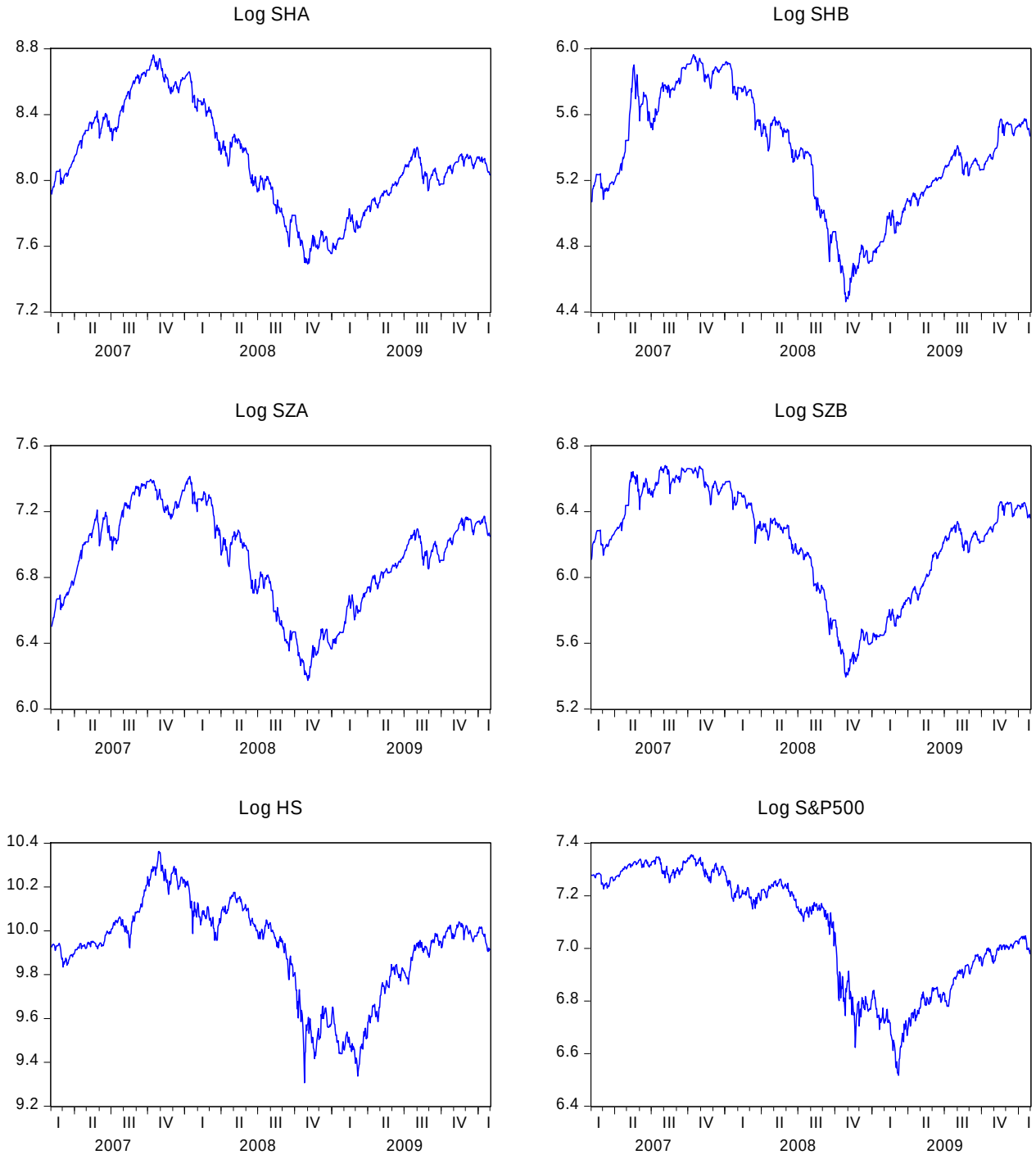

Figure 5. Log stock price indices during Subprime Financial Crisis

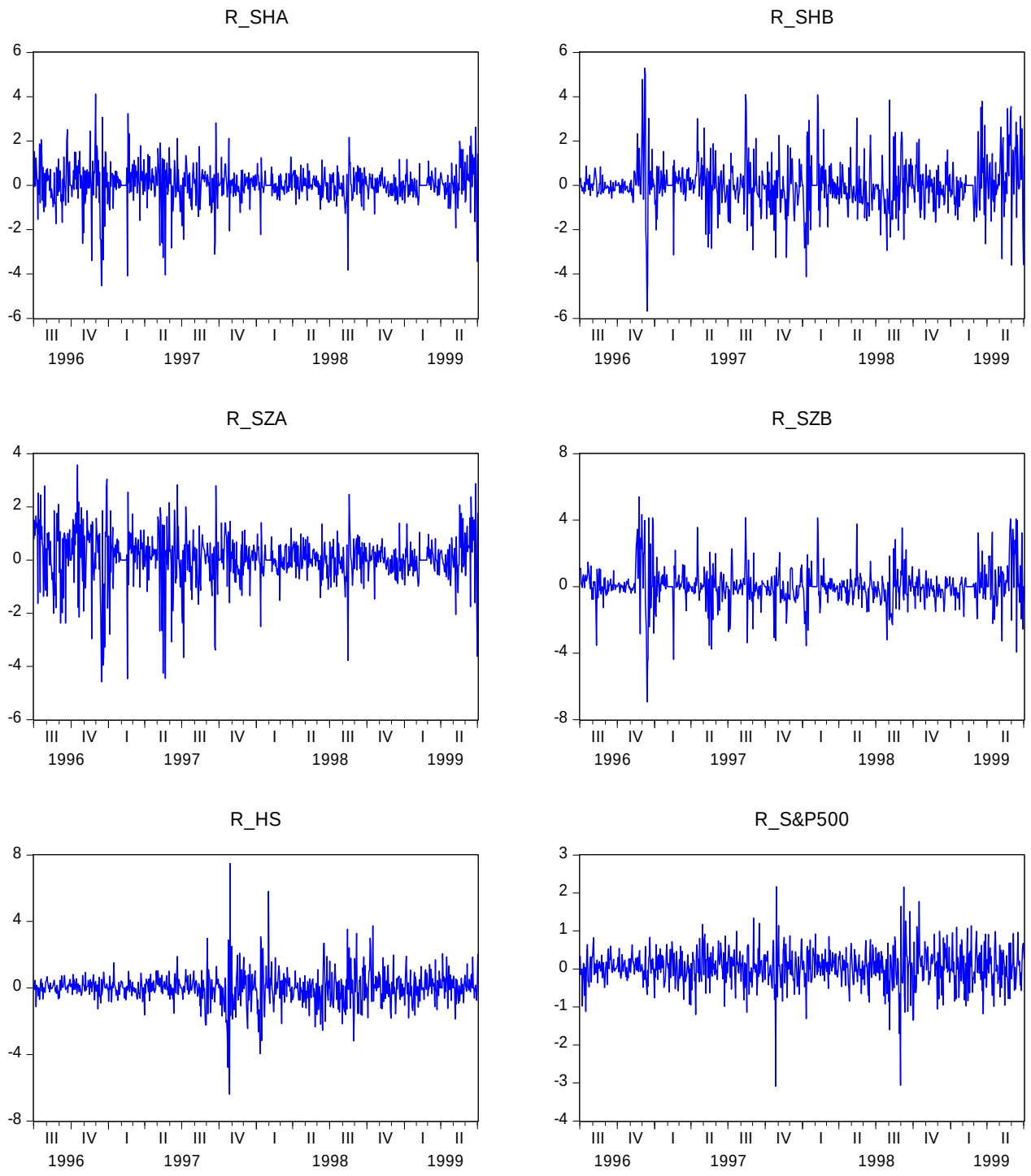

Figure 6. Returns of share price indices during Asian Financial Crisis

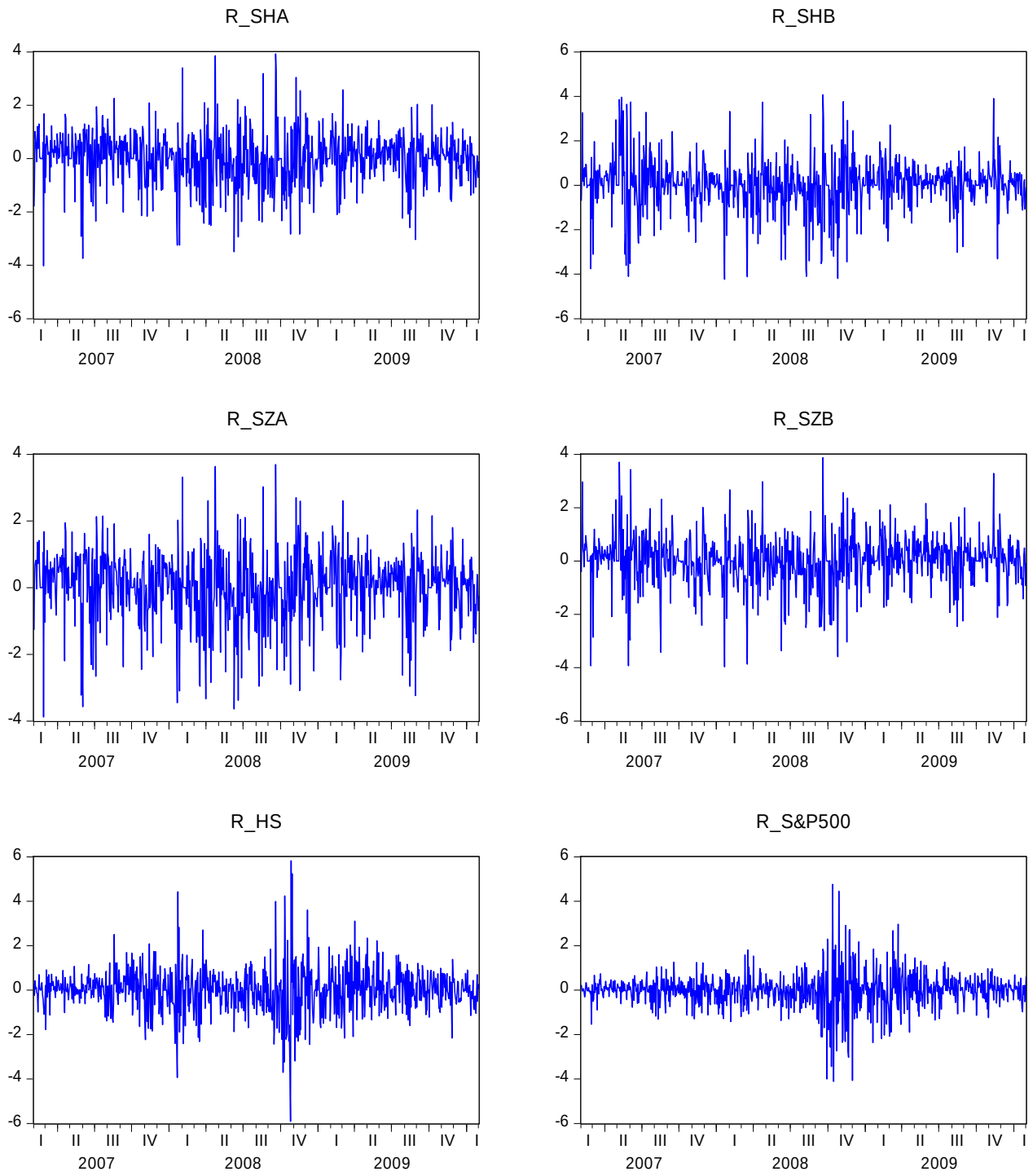

Figure 7. Returns of share price indices during Subprime Financial Crisis

Appendix B:

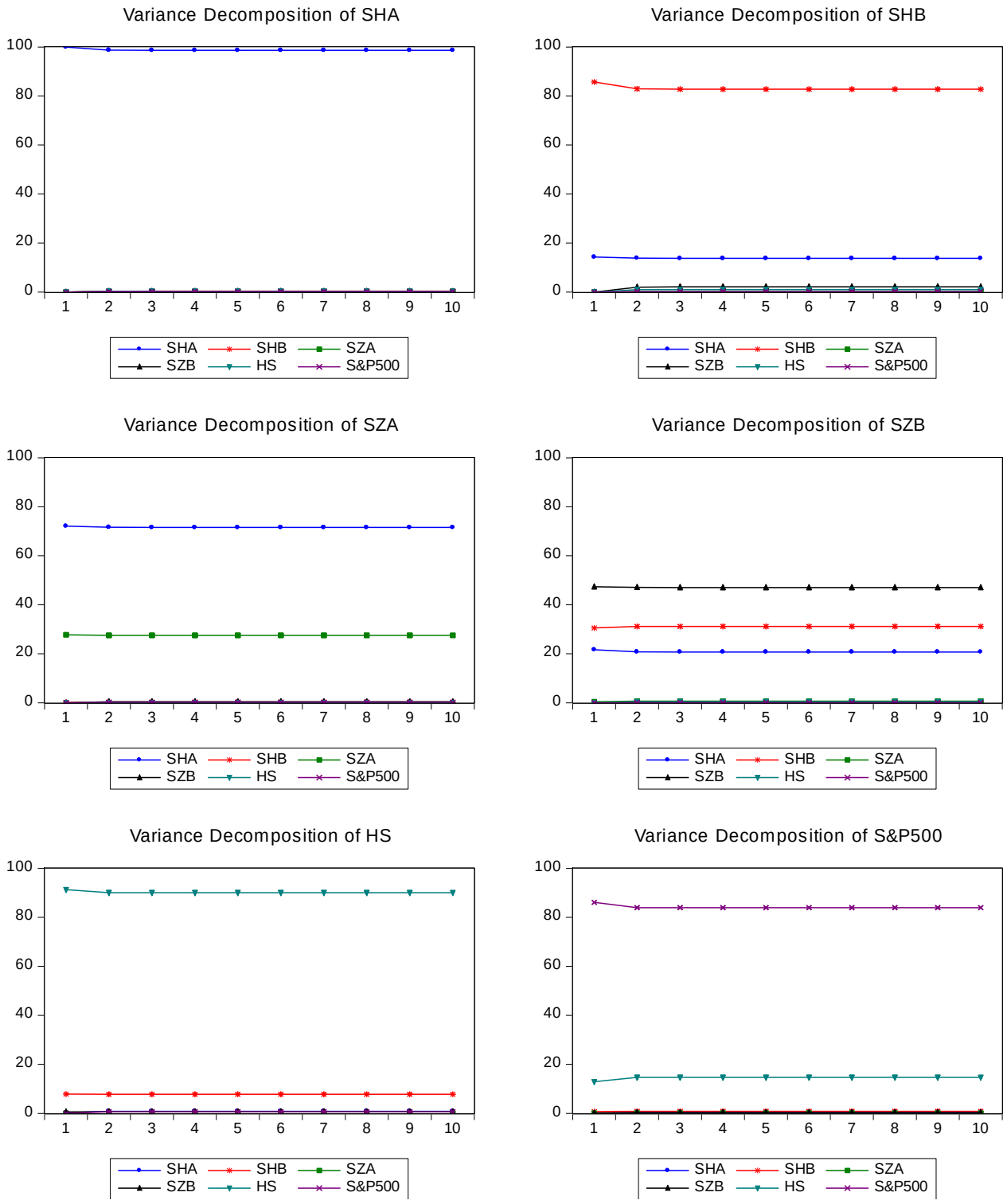

Figure 8. Variance decomposition during Asian Financial Crisis

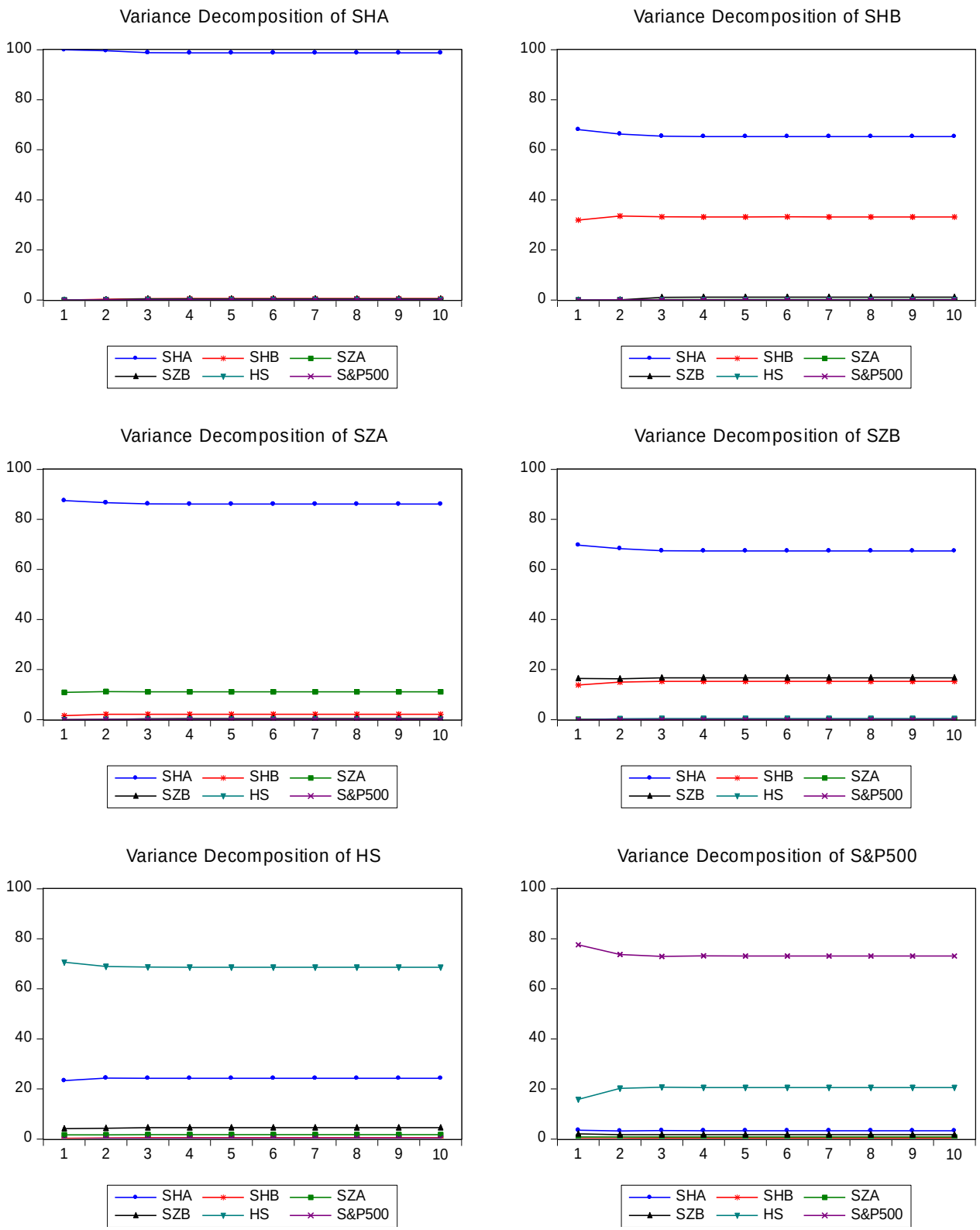

Figure 9. Variance decomposition during Subprime Financial Crisis