Asymmetric Stock-Returns Volatility Transmissions During the Asian Financial Crisis*
— the case of the ASEAN markets

by

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Abstract

This paper uses the multivariate Asymmetric Power ARCH model developed by Ding et al. (1993) to investigate the five major ASEAN stock markets in the period from 1996 to 1999, which includes the period of the Asian economic crisis in 1997. Traditionally, a two-step approach is used to examine co-movements across stock markets. A multivariate framework is considered as a better approach relative to a univariate framework. Not only does it eliminate the generated estimators problem from a two-step estimation, but also the efficiency and the power of the tests for cross-market spillovers can be substantially improved. Our analysis shows that the markets in the region were strongly dependent on their past values of returns and volatilities, suggesting that the shocks are country-specific. In particular, the asymmetric volatility transmission shows that the greater influence of negative innovations over positive ones on stock returns was significant before the crisis. However, only few price and volatility spillovers were observed in the sample.

1. Introduction

Since the first eruption of the Asian financial crisis in Thailand in July 1997, the financial sectors of most Southeast Asian countries have been hit by stormy shocks. As shown in Figure 1, these Asian stock markets crashed after the Thai baht was allowed to float. Figure 2 indicates that the stock indices in different countries plummeted simultaneously and then partially rebounded during the crisis period. In general, the evidence suggests that unexpected changes in one stock market could significantly affect price movements of another, with an indication of a high degree of co-movement across stock markets. As Forbes and Rigobon (1999a: 3) point out, "since most country risk is idiosyncratic, this high degree of co-movement suggests the existence of mechanisms through which domestic shocks are transmitted internationally." Furthermore, a series of studies suggest that a substantial degree of interdependence exists among international stock markets and that markets are affected mutually through certain transmission channels of shocks. Baig and Goldfajn (1998) investigate the impact of own-country news and cross-country news on the financial markets, and find that the news contributed to the financial instability during the crisis, with the reactions of the markets to bad news being of a greater magnitude than to good news.

Black (1976) notes that there is a negative association between the current returns and future volatility. Later, Christie (1982) uses the leverage effect to explain the asymmetric effect of shocks. A decrease in the equity value of a firm would raise its debt-to-equity ratio, thus increasing the firm's riskiness measured by higher future volatility. Therefore, the current equity return and the future volatility are negatively related. Several papers have confirmed the hypothesis of the asymmetric volatility transmission; for example, Nelson (1991), Cheung and Ng (1992), Koutmos (1992), Poon and Taylor (1992), Koutmos and Booth (1995), and Booth et al. (1997). They all find a significant leverage effect in the stock returns of national markets, i.e., the greater influence of negative innovations over positive ones.

Anomalies in stock market returns have been investigated for decades. While most of the literature has focused on stock markets in developed countries, in recent years several economists have addressed the issue for the stock markets of emerging economies, such as Asian stock markets. For example, Ho (1990) documents that most of Asian stock markets tend to have significant negative returns on Mondays and Tuesdays but positive returns on other days. Similar results can be found in Agrawal and Tandon (1994), Wong et al. (1992), Lee et al. (1990) and Lakonishok and Smidt (1988). These studies also find that January mean returns are significantly higher than that for the other months. In terms of volatility of stock returns, Ho and Cheung (1994) discover that the markets tend to be more volatile at the beginning of the week and less volatile as the weekend approaches. The results have been confirmed by Aggarwal and Rivoli (1989), Agrawal and Tandon (1994) in which they conclude that Mondays have the highest volatility during the week while Fridays the lowest. In a recent paper by Choudhry (2000), he uses a GARCH model and finds that the effects of the day of the week are significant on both stock returns and volatility among emerging Asian stock markets. Thus, the seasonal anomaly in stock markets needs to be considered when investigating the movements of the stock returns.

In the literature on examining co-movement across stock markets, several papers adopt a two-step approach to analyze the stock spillovers among the markets. Specifically, the innovations estimated in the first step are used as a proxy for the volatility measure in the second step of model estimation. Although the procedure is easy to apply, it entails some estimation drawbacks: First, the parameter estimates of the first step without spillovers may be inconsistent due to omitted variables bias. Second, the second step with spillovers involves generated variables from the first step and thus the estimated standard errors from the spillover parameter estimates are inconsistent (Pagan, 1984). Finally, only pairwise spillovers have been considered due to the limitation of the approach. Alternatively, a multivariate framework is considered as a better approach relative to a univariate framework. Not only does it eliminate the generated estimators problem from a two-step estimation, but also the efficiency and the power of the tests for cross-market spillovers can be substantially improved (Koutmos and Booth, 1995).

The purpose of this paper is to investigate the transmission mechanisms among the five major Southeast Asian stock markets: Indonesia, Malaysia, the Philippines, Singapore, and Thailand. In particular, we focus on the asymmetric response of stock returns and co-movements of the stock markets during the Asian financial crisis of 1997–98. The task is accomplished by extending the Asymmetric Power Generalized Autoregressive Conditionally Heteroskedastic (A-PGARCH) model of Ding et al. (1993) along three dimensions. First, we extend the model to a multivariate version of the A-PGARCH model to analyze the co-movements of the Southeast Asian stock markets from 1996 to 1999, which covers the Asian currency turmoil that started in July, 1997. An A-PGARCH model also facilitates an examination of the asymmetric impact of volatility transmission among the five markets.[1] Second, we assume that the error terms follow the *Student* t-distribution to account for the excess kurtosis in the returns series. Our estimate of the degrees of freedom for the t-distribution indicates that it captures leptokurtosis present in stock returns. Third, we conduct the sub-period experiments to discuss the differences in behaviors of stock returns across markets such as the price and volatility spillovers, and the leverage effect and the degree of interdependence.

Our empirical results indicate that the asymmetric effect is most pronounced before the Hong Kong market crashed. This may be due to a few economies in the region already under market stress, or to the speculation of market participants. During the turmoil period, the effect may be diluted by a high degree of government involvement in the financial markets. On the other hand, price and volatility spillovers between the markets seem not to be significant; instead own country volatilities are greatly influenced by their past values, which suggests that the shocks are country-specific. Finally, the sample correlations in all five markets are substantially increased during the crisis period, which might contribute to the investors engaging herding in their investment behavior, or to coordination of macroeconomic policy among the countries.

It is desirable to examine the spillover relationships among Southeast Asian stock markets because these countries share similarities in financial markets, industrial structure and macroeconomic policy. There is strong economic cooperation among the Southeast Asian countries. The Association of Southeast Asian Nations (ASEAN), a prominent organization for the Southeast Asian area, serves as the regional assembly to improve the economic integration and liberalization. Moreover, the tariff systems, currency systems and exchange rate policies of the ASEAN member countries are closely related by agreements and measures of the organization. In addition to substantial relationships with common international trading partners (U.S., Japan, EU, etc.), there is a significant intra-regional trade among the ASEAN countries; for example, according to the ASEAN official estimates, the share of intra-regional trade was more than 60 percent of the ASEAN's total trade in 1996 and 1997. Finally, the ASEAN countries have adopted similar trading agreements, investment practices and industrial cooperation schemes. Considering the ties among the ASEAN countries, it is important to investigate the transmission mechanisms of shocks across the countries and the dynamics of the stock markets as the "Asian flu" became full-blown in the late 1997.

The paper is organized as follows. Section 2 summarizes the theoretical and empirical work on the transmission mechanisms of international shocks in stock markets. Section 3 describes the ASEAN and the major Southeast Asian stock markets in more details. Section 4 discusses the data and examines the nature of the stock returns in order to better construct the spillover model. Section 5 advances the methodology of an A-PGARCH model. Sections 6 and 7 contain the empirical results estimated from the univariate and multivariate models, respectively. Section 8 shows sensitivity of the results by altering the definitions of the periods. Section 9 concludes the study and suggests directions for further studies. Figures and tables are provided at the end of the paper.

2. Review of Transmission Mechanisms[2]

While economists try to find the reasons for the simultaneous occurrence of crisis in many Asian countries, the term "contagion" has been used too loosely in the context of the international transmission of volatility. Before we proceed with the analysis of the data, it is necessary to distinguish different forms of transmission of shocks because each of them has different policy implications. For example, if the economic instability is caused by weak fundamentals, then we will not expect the markets to recover quickly unless the government improves domestic fundamentals. On the other hand, if the plunge of stock markets was caused mainly by the widespread fear and herd behavior of investors, the government should establish its credibility to pacify market sentiments. Offsetting the distortions of markets is the only solution to eliminating the impacts of financial turmoil.

The theoretical literature which explains the concurrent movements of markets can be roughly summarized into three categories:[3] (1) "monsoonal effects" are caused by aggregate shocks which affect the economic fundamentals across countries; (2) "spillovers" result from country-specific shocks which affect macroeconomic fundamentals of neighboring countries; and (3) "pure contagion" refers to shocks which are not related to changes of the country's fundamentals.

The first category explains how aggregate shocks can simultaneously affect the fundamentals of different countries. For example, the announcement of an increase in the U.S. interest rates would reduce the supply of international capital, which in turn could halt the growth of many Asian countries, since most of them heavily depend on either foreign loans or foreign investments. The stock markets in the region could be affected by the aggregate shock, and price changes would follow the same path of movements. Consequently, the linkage across countries becomes significant after the shock.

The second category focuses on country-specific shocks in which a shock to a country can be transmitted into changes in fundamentals of several different economies. The channels of transmission could be through the real linkages of economies, such as different policy regimes. For example, if a country imposes a trade tariff on importable goods, the result could be a contraction of exporting sectors in trading countries accompanied by slowed growth. Thus, these economies are linked through a trade policy.

The last category addresses any unexpected changes in markets that cannot be explained by the previous two mechanisms. It may be due to shifts in multiple equilibria or changes in self-fulfilling expectations driven by investor psychology (Masson, 1998), a liquidity shock in the capital market to investors (Valdés, 1996), the herd behavior of investors (Calvo, 1996), or changing political economy (Drazen, 1998).

In general, although these mechanisms affect economies in different ways, they have at least one commonality as Forbes and Rigobon (1999a) comment: the correlations across countries during financial crises are different than those during economic tranquility. The international transmissions are strengthened during large swings in the financial markets.

In the empirical literature on financial crises, economists focus on estimating the magnitude of transmission mechanisms. Three approaches are commonly used and they are summarized below.

The first approach involves the direct estimation of transmission mechanisms. The contagion coefficients are estimated using the transmission channel of news across countries. For example, Baig and Goldfajn (1998) use daily news regarding market performance from major mass media, such as Reuters, Financial Times and CNN, to test the contagion effects of stock markets in several East Asian countries during the Asian financial crisis. They find that a country's news has substantial impacts on stock markets in the region, with indication of cross-country contagion in stock markets.

The second approach is to test changes in the variance-covariance matrix that summarizes the transmission channels. King and Wadhwani (1990) test for the stock market linkages between U.S., U.K. and Japan. They find that the correlation between New York and London stock markets rises significantly during the stock market crash in 1987. Thus, they conclude that contagion effects occur during periods of economic tumult. Lee and Kim (1993) examine returns of twelve major stock indices from August 1984 to December 1990 and find that the stock markets became more interdependent after the October 1987 crash. For example, the average correlation coefficients for weekly stock returns across markets rises to 0.39 in the post-crash period as compared to 0.23 before the crash. They consider the increased correlations as evidence of contagion.

In the third approach, the transmission mechanism is measured as the transmission of volatility using a GARCH model. Hamao et al. (1990) report that there are significant cross-market spillover effects and that the international transmission of volatility does not spread evenly across countries. For example, they find that a shock from the Japanese market does not significantly affect stock prices in the U.S. or U.K. markets. However, the estimation approach they use is subject to the generated regressors problem; so some caution must be exercised in interpreting their results.

Some studies consider contagion effects as a function of stock returns across markets and focus on the vulnerability of a country to shocks from other countries using a vector autoregression (VAR) framework. Eun and Shim (1989) investigate the international transmission mechanism of stock market movements by estimating a nine-market VAR system. They find that a substantial amount of interdependence exists among national stock markets, and that the U.S. stock market is the most influential market in the world. Thus, any changes in the New York stock exchanges would cause fluctuations of stock markets across countries. Tan (1998) advances a vector error correction model (VECM) to capture fundamentals and herd behavior contagion. In using this framework, he discovers that the concurrent crash in stock markets during the Asian crisis can be explained by contagion effects. In addition, he highlights the policy implications of country-specific contagion in stock markets.

Finally, a number of studies investigate the co-movement between stock markets in the long-run relationship instead of changes in the short-run dynamics. Unlike the procedures described above by estimating the variance-covariance matrix, the econometric methodology is grounded on testing for changes in the co-integrating relationship between stock markets. For example, Cashin et al. (1995) investigate the degree of international integration in industrial and emerging stock markets from 1989 to 1995. They use cointegration analysis and find that the correlation of stock prices across countries tend to rise in the long run.

3. ASEAN and Southeast Asian Stock Markets[4]

The Association of Southeast Asian Nations was founded on August 8, 1967 by the five original member countries, Indonesia, Malaysia, the Philippines, Singapore, and Thailand. By 1999, five more countries had joined the association: Brunei, Vietnam, Laos, Myanmar and Cambodia. The ASEAN region covers a total area of 4.5 million square kilometers and has a population of about 500 million, with the gross domestic product of US$737 billion and a total trade of US$720 billion. The objectives of the ASEAN are to improve the economic growth, social progress and cultural development in the region through the joint cooperation of member countries, and to promote the regional security and stability without interfering with the domestic law and regulations among the countries. In order to achieve the regional economic integration, several measures on trade and investment liberalization have been adopted. The Preferential Trading Arrangement of 1977 entitles the member countries to a preferential tariff system for trade. The Framework Agreement on Enhancing Economic Cooperation of 1992 initiates the creation of an ASEAN Free Trade Area (or AFTA) to enhance the region's competitive advantage for trade. The ASEAN Vision 2020 adopted in 1997 called for a further regional economic integration and aimed at creating an ASEAN Economic Region where there is a free trade in goods, capital, services and investments.

Table 1 shows some basic information for the five Southeast Asian stock markets from 1996 to 1999. As it can be seen, Malaysia had the largest stock market in the region: by the eruption of the financial turmoil, the trading value of the stocks listed in Malaysia was more than half of that in the Southeast Asian stock markets. Singapore supplanted Malaysia and became the leading stock market after the region was beset by the financial unrest in 1997. Still, Malaysia had the largest number of listed firms in the stock market during the period while Indonesia and the Philippines had the smallest markets. In general, the statistics in the table also indicate that the impact of the financial turmoil on the markets was unprecedented and devastating: the value of the markets in 1998, except for Singapore, shrank by more than half. Furthermore, the market capitalizations in Indonesia, Malaysia and Thailand were less than one-third of the values in 1996. Finally, it is noteworthy that the turnover rates in these markets are relatively higher in magnitude, which indirectly implies that there are speculators with short investment horizons in these markets. In the presence of short-term speculation this can result in some forms of market inefficiencies (Froot et al., 1992).

These countries are also very close in terms of geographic locations. Four markets are within one time zone and Thailand is located in the adjacent time zone. Therefore, the trading time for the markets are about the same (Table 2) and the problems of perfect nonsynchronous trading can be minimized.

4. Data and Preliminary Findings

Data used in this paper are the daily closing stock price indices of the Indonesia, Malaysia, the Philippines, Singapore and Thailand, obtained from Datastream. The indices used are Jakarta stock exchange composite index for Indonesia, Kuala Lumpur composite price index for Malaysia, the Philippines stock exchange composite index for the Philippines, Singapore all-Singapore equities price index for Singapore and Bangkok stock exchange of Thailand index for Thailand. All the indices are value-weighted and are converted to U.S. dollars. The daily return for each index at time t in country i, $R_{i,t}$, is the continuously compounded returns calculated as $R_{i,t} = \log(P_{i,t}/P_{i,t-1})$, where the stock price index in country $i$at time t is represented by $P_{i,t}$. The data range from January 1, 1996 to December 31, 1999. In order to examine the stock price behavior in global conditions, we divide the sample into three sub-periods to analyze the issue.

It is difficult to ascertain the exact timing of the Asian crisis, but as Forbes and Rigobon (1999a) pointed out, "The press paid little attention to the earlier movements in the Thai and Indonesian markets (and, in fact, paid little attention to any movements in the stock markets in East Asia) until the mid-October crash in Hong Kong." (p. 16) After the Hong Kong market plummeted, the catastrophic financial crisis in Asia started to draw the world investors' attention, followed by a flight of foreign capital, which further withered the shaking stock markets. Therefore, for our benchmark analysis, we define the crisis period starting from the time when the Hong Kong market first crashed in mid-October of 1997. In addition, several news sources and official announcements maintained that the markets have showed the sign of stabilization in early 1998.[5] In particular, on March 1st of 1998 the major Asian economies have gained some strength which was expected to boost the feeble financial markets in Southeast Asia.[6] Thus we use March 1 of 1998 to mark the stability period after the crisis. Since the definitions of the sub-periods might be somewhat arbitrary, we will re-examine the results by conducting sub-period tests in later section.

For the benchmark case, we identify October 17, 1997 to March 1, 1998 as the turmoil/crisis period, from January 1, 1996 to October 16, 1997 as the pre-crisis period, and March 2, 1998 to the end of 1999 as the post-crisis period.

Figures 3 and 4 show the movement of daily stock returns and their absolute values from 1996 to 1999, where the shaded area denotes the defined crisis period. By the second half of 1997, the returns in most of the markets remain relatively stable, followed by extreme ups and downs for the next two years. From Figure 4, the movements of the absolute values of returns indicate the stylized fact of volatility clustering. That is, large absolute returns tend to be followed by a large absolute return. This feature became more manifest from the second half of 1997 to the first half of 1998. That stock return volatility is changing over time suggests that an ARCH/GARCH type model is appropriate for the returns series to capture the time-varying volatility property. Figure 4 also reveals that while the volatilities in most of markets after the crisis period are higher than in any other periods, the largest variance of stock returns appears during the crisis period (except that the peak in Malaysia emerges during the post-crisis period). By early 1999, several markets have shown signs of recovery as the market volatilities started tapering off. In general, the magnitude of the volatility of the stock returns is higher during the second half of our sample (pre-crisis period) than those during the first half (post-crisis period).

Tables 3 through 6 summarize the descriptive statistics for stock returns for the benchmark case. In general, it is shown that most stock markets in the region have suffered a large setback by the Asian crisis. For example, Table 3 illustrates that the estimates of mean and median for the continuously compounded stock returns are negative throughout the whole sample period, except for Singapore which realizes marginally positive returns. The excess kurtosis and skewness statistics for the returns suggest that the distributions are not normal but rather fat-tailed. In other words, all series are leptokurtic and skewed. So, it is not surprising to see that all five returns fail the Jarque-Bera normality test at any sensible levels of significance. Moreover, statistics for the Ljung-Box tests are all significant under the 5% level indicate that there is a significant linear and a non-linear dependencies in the returns of all five markets. Linear dependencies may be due either to the imperfect synchronous trading time among the markets (Scholes and Williams, 1977; Lo and MacKinley, 1988), or to a certain degree of market inefficiency (Fama, 1991). Non-linear dependencies may contribute to ARCH effects (time-varying volatility) as suggested by the findings of several studies on the stock returns (Akgiray, 1989; Nelson, 1991; Booth et al., 1992). We also conduct the Phillips-Perron unit root tests to verify that the returns series are stationary, which are confirmed by the significance of the test statistics under the 5% level.

During the pre-crash period (Table 4), the returns for the markets are negative except for Indonesia and Singapore where the medians are marginally positive. While the eruption of the financial turmoil in Thailand began affecting Malaysia and the Philippines, Indonesia and Singapore were immunized from the regional disturbances.[7] However, later in the turmoil period, as presented in Table 5, all of the markets were suffering from the set-back of the financial crisis by the end of 1997 to the early 1998, with the estimates of mean and median returns being negative. Another striking feature during this period was that the markets became more volatile as measured by the standard deviations. In particular, the standard deviations for Indonesia, Malaysia and Singapore were three times more than those in the tranquil period.

By the second quarter of 1998, the Southeast Asian countries began recovering from the economic disorders. First of all, two markets exhibit positive returns as shown in Table 6. Even though the returns in Malaysia, the Philippines and Thailand are still negative, the magnitudes are much smaller than what they were during the crisis. Also, the market volatilities are less than those in the turmoil period, although the standard deviations are still higher than the estimates before the crisis erupted. In general, these signs indicate that the markets were stabilizing, although the aftermath of the financial crisis still made the economic outlook somewhat fragile.

To complete the analysis, we also investigate the behavior of various stock market anomalies such as the day-of-the-week effect and the monthly effect in the returns series. The purpose of this investigation is two-fold. We first examine if any systematic movements of stock markets do exist as discovered by several studies. Then we can determine whether seasonal dummies are needed to be included in the model specification. Also, instead of including all the days during the week and all months during the year, we will only add the significant seasonal factors, if there is any, in the model in order to increase the degrees of freedom. As we summarize in Tables 7 to 11,[8] only a few of the day-of-the-week or the months are significant using either 5% or 10% significance level. For example, during the pre-crash period, Table 7 suggests that mean returns for Mondays are the lowest in all cases and significantly so in all but Indonesia. Friday provides the highest mean in Malaysia, the Philippines and Singapore, but the effect is not significant at any sensible levels. To explain the day-of-the-week effect and the weekend (Monday) effect, Fortune (1991) indicates that good news is likely to be released during the market's trading hours and firms and governments would not disclose bad news until the close on Friday. Thus, the earliest time investors can first react to bad news is the following Monday.

The highest standard deviation on Mondays is found in the cases of Singapore and Thailand, this may be due to the fact that the information advantage of informed investors reaches the maximum on Mondays (French and Roll, 1986; Barclay et al., 1990; Foster and Viswanathan, 1990). On the other hand, Tuesday has the lowest standard deviation in all cases except that of the Philippines. For the crisis period, the results in Table 8 show a different picture. The lowest mean returns tend to fall on Thursday in most cases while Wednesday has the highest. However, the day-of-the-week effect is not significant in all markets and the Thursday effect is marginally significant only for the Philippines market. Monday is likely to produce the highest standard deviation for the Philippines, Singapore and Thailand while Friday gives the lowest for most of the markets except Indonesia and the Philippines. The results in the post-crash period (Table 9) are similar to those in the pre-crash period.

For the monthly analysis, the results are mixed.[9] By the advent of the collapse of the Hong Kong market, January is more likely to be lucrative than any other months but August tends to be more volatile in the stock returns (Table 10). The January effect may be due to the tax-loss selling hypothesis and the small firm effect (Roll, 1983).[10] After the crisis, Table 11 shows that the returns in October are significantly higher while August has the lowest mean returns for all five markets. Moreover, January has the highest volatility while December and February tend to be more stable in each market's returns.

Although the results in this section are preliminary, they provide a basic view on the returns series and help enrich the model we will employ in later analysis. In the next section, a generalized version of the ARCH model will be introduced to analyze the interactions between the ASEAN stock markets.

5. Econometric Methodology

In the financial literature, it has been suggested that the autoregressive conditional heteroskedastic (ARCH) models are well suited to capture stock return movements.[11] The distribution of percentage changes in stock prices tends to have fatter tails than a normal distribution, and the ARCH models can capture this property by allowing for changing conditional variances. The ARCH model was first developed by Engle (1982) and then generalized as the GARCH (Generalized ARCH) model by Bollerslev (1986). In further developments, Taylor (1986) observes that absolute returns can be significantly serially correlated over long lags. He then modifies the ARCH type specifications by modeling the conditional standard deviation function instead of conditional variance. Then Schwert (1989) argues that the conditional standard deviation should be linearly dependent on lagged absolute residuals. Finally, Ding et al. (1993) propose a generalized version of the ARCH model, the Asymmetric Power ARCH (A-PARCH) model, which nests several ARCH-class models and Taylor/Schwert specifications.[12] Unlike the traditional ARCH models that is based on the squared errors, the standard deviation specification of the A-PARCH model not only avoids exaggerating the impacts of outliers in the series, but also makes the non-linear optimization readily reach convergence because the model itself is linear in variables.

Denote $R_{i,t}, i = 1, \ldots, 5$ (i.e., $1 =$ Indonesia, $2 =$ Malaysia, $3 =$ Philippines, $4 =$ Singapore and $5 =$ Thailand) as the return for market i at time t. Variable Ω_{t-1} is the information set up to and including time $t-1$; $\sigma_{i,t}$, $\sigma_{i,j,t}$ and $\rho_{i,j}$ are the conditional variance, conditional covariance, and correlation coefficient, respectively; $\epsilon_{i,t}$ is the innovation at time t. An A-PARCH(p, q, d) model with a MA(1) process, which describes spillover and asymmetric effects among the markets, takes the form:

$$R_{i,t} = c_i + \sum_{j=1}^{5} \phi_{i,j}\epsilon_{j,t-1} + \epsilon_{i,t} \quad \text{for } i, j = 1, \ldots, 5,\ t = 1, \ldots, n \tag{1}$$

$$R_{i,t} = \log(P_{i,t}/P_{i,t-1}) \times 100$$

$$\underline{\epsilon}_t|\Omega_{t-1} \sim \textit{Student-t}\ (0, H_t, \nu) \tag{2}$$

$$\sigma^d_{i,t} = a_i + \sum_{l=1}^{p} \alpha_i (|\epsilon_{i,t-l}| + \gamma_i \epsilon_{i,t-l})^d + \sum_{m=1}^{q} \beta_i \sigma^d_{i,t-m} \quad \text{for } i = 1, \ldots, 5 \tag{3}$$

$$\sigma_{i,j,t} = \rho_{i,j} \sigma_{i,t} \sigma_{j,t} \quad \text{for } i, j = 1, \ldots, 5 \quad \text{and} \quad i \neq j \tag{4}$$

where H_t is the conditional covariance matrix of the error vector, $\underline{\epsilon}_t = [\epsilon_{1,t}, \ldots, \epsilon_{5,t}]'$, and ν is the degrees of freedom parameter for the *Student-t* distribution. Bollerslev (1987) and Baillie and Bollerslev (1989) argue that the Student t-distribution can capture the fat-tail of the returns series by allowing more outliers along with the ARCH effect. Moreover, when the degrees of freedom parameter (ν) is greater than 4, the Student t-distribution is proved to be appropriate to account for the excess kurtosis (Baillie and Bollerslev, 1995).[13]

Equation (1) models the stock returns of the five markets with a moving average (MA) structure. Specifically, the stock returns of each market is influenced by both its own past shocks and the disturbances from foreign markets, which are incorporated in the information set $\Omega_{i,t-1}$ for $i = 1, \ldots, 5$. Any movements in market j will be absorbed in the information set of the investors in market i. For example, the investors in Indonesia will make their investment decisions based on the trading information from Hong Kong or other neighboring countries. Thus, the domestic stock prices are partly determined by innovations from other markets, with the coefficients, $\phi_{i,j}$ for $i \neq j$, capturing the price spillover effect across markets. Variable $\phi_{i,j}$ for $i = j$ reflects the extent of the influence of the past innovations of its own market, with autocorrelation in the returns fully allowed.

In equation (3), the standard ARCH and GARCH effects are estimated by α_i and β_i, respectively. Since β_i in the analysis is not equal to zero, equation (3) is referred to as an asymmetric power GARCH (A-PGARCH) model, which is slightly different from the original A-PARCH model developed by Ding et al. (1993) where the GARCH term is zero. The coefficient, γ_i, captures the leverage effect which accounts for the asymmetric response of volatility. The asymmetric effect is present if γ_i is negative and significant. It is modeled in the way to reflect the greater impact of negative shocks than positive shocks since the magnitude of shocks is $(\epsilon_{i,t} + \gamma_i \epsilon_{i,t})$ for bad news $(\epsilon_{i,t} < 0)$ and is $(\epsilon_{i,t} - \gamma_i \epsilon_{i,t})$ for good news $(\epsilon_{i,t} > 0)$. The term, $(|\epsilon_{i,t}| + \gamma_i \epsilon_{i,t})$, captures the size of shocks in which $(\gamma_i \epsilon_{i,t})$ captures the sign effect of corresponding shocks. Thus, a negative $\epsilon_{i,t}$ with a negative γ_i tends to strengthen the size of shocks while a positive $\epsilon_{i,t}$ tends to neutralize it.

The power term is denoted by d in equation (3) and can be given by any positive values. In particular, Ding et al. (1993) conclude that when $d = 1$ the long-memory property of stock returns is the strongest comparing to other values of d. In addition, Brooks et al. (2000) find that the estimated power terms for 10 countries are not significantly different from one but are significantly different from 2. Therefore, we will use the unity power term ($d = 1$) for analysis. The parameters of the volatility spillovers across markets are measured by $\rho_{i,j} \times \alpha_{i,1} \times \alpha_{j,1}$ for $i, j = 1, \ldots, 5$. The derivation is sketched in Appendix A.

Equation (4) specifies the conditional covariance with the assumption of constant conditional correlations (CCC) as proposed by Bollerslev (1990). Basically, conditional variances and covariances are assumed to be time varying, but conditional correlations are constant over time. Although its validity needs to be further assessed, Bollerslev (1990) argues that this assumption greatly simplifies the complexity of estimation and ensures the positive definiteness of covariance matrices. Finally, the likelihood function with the Student t-distribution is shown in Appendix B.

6. Univariate Results

The original A-PARCH model assumes that the conditional error term follows a white noise process. On the other hand, some studies (Scholes and Williams, 1977; Cohen et al., 1980) find that stock returns are serially correlated over time. Thus, a first-order moving average, MA(1), will be introduced into the model to account for the autocorrelation in the excess returns. To include the holiday and the day-of-the-week effects in the markets in question, seasonal dummy variables are added in both the conditional mean and variance equations. Moreover, it is well known that short-term nominal interest rates are a good predictor of future volatility in stock returns since the movements of interest rates reflect expectations about inflation which is a key factor in the movements of stock markets (Fischer, 1981; Glosten et al., 1993). In particular, many of the Southeast Asian countries are heavily indebted with foreign loans: Higher interest rates would lead to higher debt-to-equity ratios and thus higher volatilities in equities markets. Higher interest rates also drive foreign capital out of emerging market equities and slow down the regional economic growth. For example, a relevant quote from the Asian Recovery report (2000) states "…rising US interest rates have triggered downward adjustments in global equity markets, which, in general, have had an adverse impact on the regional (Asian) markets…" (p. 4).

Based on the arguments above, we consider the following univariate A-PGARCH (1,1,1) model with a MA(1) process for the mean equation:[14]

$$\begin{aligned}R_{i,t} &= c_i + \phi_{i1} HOL_{i,t} + \sum_{d=1}^{7} \zeta_{id} DAY_{i,t} + \sum_{m=1}^{12} \eta_{im} MONTH_{i,t} \\ &\quad + \lambda_i \epsilon_{i,t-1} + \epsilon_{i,t} \qquad (5) \\ &\quad \text{for } i = 1, \ldots, 5\end{aligned}$$

$$\begin{aligned}\sigma_{i,t} &= a_i + \alpha_{i1}(|\epsilon_{i,t-1}| + \gamma_i \epsilon_{i,t-1}) + \alpha_{i2}\sigma_{i,t-1} + \alpha_{i3} HOL_{i,t} \\ &\quad + \sum_{d=1}^{7} \beta_{id} DAY_{i,t} + \sum_{m=1}^{12} \delta_{im} MONTH_{i,t} + \alpha_{i4} USTB3M_{i,t} \qquad (6) \\ &\quad \text{for } i = 1, \ldots, 5\end{aligned}$$

where

$$\begin{aligned}HOL_{i,t} &= 1 \text{ if the first trading day after a holiday; } = 0 \text{ otherwise} \\ DAY_{i,t} &= \text{the day-of-the-week dummies} \\ MONTH_{i,t} &= \text{the monthly dummies} \\ USTB3M_{i,t} &= \text{the 3-month U.S. treasury bill rates}\end{aligned}$$

In this section, we focus on the following questions: (1) Is an A-PGARCH model well-suited for modeling the returns series? (2) Is the leverage term, γ_i, significant in the model? (3) Do the seasonal dummies help explain the return movements after accounting for ARCH effects? (4) Which seasonal dummies are commonly and significantly affecting the markets across countries? (5) Do the patterns of return movement vary across the three different periods defined earlier in the paper? By answering these questions, it helps us refine the multivariate specification of the model without adding redundant variables. Thus, the model will be parsimonious and will have a greater power for the analysis at hand by increasing the degrees of the freedom in estimation.

The estimates from the univariate A-PGARCH model (equations (5)–(6)) during the three different periods are presented in Tables 12 to 14. For the pre-crisis period (Table 12), the moving average coefficients are all significant at either the 5% or the 10% level in all five markets, suggesting that either imperfect synchronous trading or market inefficiency induces autocorrelation in the return series. For the conditional variance which describes the short-term dynamics of the markets, the ARCH and GARCH terms are all significant at the 5% level, indicating that the markets are strongly affected by their past values of innovations and volatilities. The leverage effect, or asymmetric impact of past innovations on current volatility, is significant in all cases, with Singapore being the exception, confirming our proposition that volatility transmission is asymmetric across the markets, that is, an unexpected negative return shock will increase predictable volatility more than an unexpected positive return shock of equal magnitude. The relative asymmetry, measured by γ_i in the model, is highest in the Indonesia, Malaysia and the Philippines markets, followed by the Thailand market. Volatility persistence, measured by the coefficients on the GARCH terms, is the highest in Thailand, followed by the Philippines, Malaysia, Indonesia and Singapore. Among the significant seasonal dummies at the 5% level, it seems that all the markets tend to have negative returns on Mondays (except for the Indonesian market). For the holiday and U.S. interest rates variables, they don't have any significant impact on the stock markets. It could be because interest rates don't affect the short-term dynamics of the stock returns and in the presence of the ARCH effect the holiday effect doesn't seem to be relatively important. The estimated Ljung-Box statistics for the standardized and the squared standardized residuals show that the A-PGARCH model is appropriate to describe the linear and non-linear dependencies in the returns series. None of the LM statistics is significant under the 5% level, implying that no other ARCH effects are left with the A-PGARCH model.

Table 13 gives the estimates during the turmoil period. The most striking difference from the result of the previous period is that none of the leverage terms is significant at the 5% level, except that the coefficient for the Singapore market is marginally significant at the 10% level. The result seems to be counter-intuitive, but it can be justified for two reasons. As Bollerslev et al. (1992) have suggested, there may be a few extreme observations which makes the leverage effect pronounced before the crisis period, and the observations may be associated with the fact that Thailand and Indonesia started suffering from the collapse of their currencies. After October of 1997, the event has widely spread among the Southeast Asian economies so that all the markets became very volatile and the excessive number of extreme observations reduced the significance of the asymmetric response of volatility to innovations. From the point of view of economic agents, before the Hong Kong market crashed, some of the investors may have anticipated the incoming financial turmoil and adjusted their expectations about the future. Thus, the investors are relatively sensitive to any bad news than to good news before the markets became unstable. When the financial crisis strikes the economy, the investors have already finished adjusting their portfolio positions. Hence, any market advances or retreats have relatively less influences on investment decisions of investors. Another possible explanation is the frequent government interventions which are commonly used by the authorities in developing countries, either through using monetary instruments or through making a large amount of direct buying or selling in the financial markets. In this way, it would smooth out the fluctuations of market movements.

Some of the leverage terms are significant in the post-crash period, as reported in Table 14. On the other hand, the leverage effect is still not significant at any sensible levels in Indonesia and Thailand, which suggests that most of the markets are still susceptible to the shocks after the Asian crisis.

To further assess the relative importance of the seasonal dummies, we apply the Akiake Information Criterion (AIC) and the Schwarz's Bayes Information Criterion (BIC) to resolve the model selection question. The difference between two criteria is that the latter (BIC) tends to impose a larger penalty on the additional variables included in the model. By the rule of thumb, the preferred model has the lowest AIC or BIC value. The values of AIC and BIC from three different specifications of the model for each market are reported in Table 15, and the values in the shaded areas represent the optimal model based on each criteria. As we can see from the table, in some cases AIC tends to select the model with more variables in the specification. On the other hand, the basic A-PGARCH specification is considered as the best one by the same criteria; for example, in the cases of Malaysia and the Philippines during the pre-crash period, Indonesia, the Philippines and Singapore during the crisis period. Also, based on the BIC criterion, it consistently chooses Model A (without including any seasonal dummies, holiday and interest rates variables) for all cases in any periods. So, this could suggest that the seasonal effects, along with the holiday effect and the short-term interest rates, may not have any deterministic impacts on the movements of the stock returns and we will use the basic A-PGARCH model for further analysis. Additionally, Doornik and Ooms (2000) show that adding a dummy variable could cause the multimodality in the GARCH likelihood estimation. In some sense, a dummy variable would make the surface of likelihood function too flat, so that the estimation algorithm may fail to reach the global maxima. Therefore, we will leave out seasonal dummies from the multivariate version of the model.

7. Multivariate Results

Table 16 provides maximum likelihood estimates of equations (1)–(4) for the pre-crash period. The first moment interdependencies are indicated by ϕ_{ij} in Table 16. There is a significant linear dependence in Indonesia ($i = j = 1$) and price spillovers from Indonesia to the Philippines ($i = 3,\ j = 1$). The former may result from either time-varying risk premia (Booth et al., 1997), or the market inefficiency (Fama, 1991). The one-way price spillover between Indonesia and the Philippines indicates that there is no feedback effect between the two markets.

The extent of the market dependence on their own past innovations is measured by $\alpha_{ij},\ i = j$. Contrary to the results from the return equation, all of the markets are strongly affected by their own shocks in the last period. The dependence is highest in Singapore, followed by Thailand, Malaysia, Indonesia and the Philippines. The extent of volatility spillovers between markets is indicated by $\alpha_{ij},\ i \neq j$.[15] The volatility spillovers are positively correlated between markets, meaning that a higher volatility in one market tends to increase the volatility in another. However, the magnitudes of the volatility spillovers are relatively smaller than those of the price spillovers.

The degree of the volatility persistence is measured by β_i in the model. Among the markets, the volatility in the Philippines market is most persistent and is the least in the Singapore market. The relative magnitude of asymmetry can be estimated by γ_i presented in Table 16. The results indicate that there are significant leverage effects among all the markets. In other words, these markets are vulnerable to bad news, as the negative shocks would greatly raise the market volatility than positive shocks. The Indonesian market is most sensitive to bad news, then followed by Malaysia, the Philippines and Thailand. The Singapore market is relatively less reactive to negative shocks. This result seems to indicate that the markets in the developing countries are more vulnerable to unexpected negative shocks because the traders are not well-informed and the market information is not readily obtainable. Any significant market retreats would be considered a bad signal to the future economic prospects and affect the market sentiments.

The results change substantially when we look at the estimates for the turmoil period, which are presented in Table 17. The price and volatility spillovers have disappeared from the markets, although there is a slightly significant price spillover from Thailand to the Philippines. In all five markets the leverage effect is not significant either. However, if we look at the sample correlations by comparing Tables 16 and 17, they are significantly higher for the turmoil period. This may be caused by the market sentiments that shifts due to the sudden change of regional economic environments, or by the fact that the ASEAN coordinated its member countries' macroeconomic and monetary policies to resolve the regional uproar. The former can be further explained by herd behavior of the investors. Chang et al. (2000) document that the lack of reliable and up-to-date firm-specific information forces the investors to focus more on macroeconomic information. Thus, the investors will engage in herd behavior in their decision making process of investment. Herding tends to exist in the emerging markets and is most pronounced during periods of extreme market movements. This is considered as evidence of market inefficiencies which can be eliminated by improving the quality of macroeconomic information. Finally, the Philippines and Singapore have the largest increase in sample correlations. In particular, the sample correlation between the Philippines and Thailand increases from 0.14 to 0.63, and from 0.24 to 0.58 between Singapore and Thailand.

For the post-crisis period, the results presented in Table 18 suggest that the transmission channels have resumed between markets. First of all, there are price spillovers from Singapore to the Philippines and to Thailand, from the Philippines to Malaysia, and from Malaysia to Singapore. Also, each market volatility is strongly subject to changes in its past values of innovations and volatilities as what we have seen in the first stability period. However, unlike the pre-crash period, although the asymmetric effect is significant for the Indonesian and the Malaysian markets, the rest of the markets are relatively insensitive to bad news. In the sense, the impacts of market retreats and market advances become qualitatively identical for the Philippines, Singapore and Thailand. In terms of sample correlations between markets, the degree of the interdependence has reduced after the financial crisis, except for Indonesia and Thailand where they remain the same extent of cohesion as that during the crisis. For most of the ASEAN stock markets, the degree of interdependence is slightly lower after the crisis as opposed to the pre-crisis level.

8. Sensitivity Analysis

Since the partition of the sample for each sub-period may be somewhat arbitrary, and we use the date when the Hong Kong market plummeted as the break point between pre-crisis and crisis periods, we need to further assess robustness of the results discussed in the previous section to complete the analysis. In this section we conduct a sensitivity test by modifying the definitions for the periods of turmoil, pre- and post-crisis. In our benchmark case, the turmoil period covers from October 17, 1997 (when Hong Kong crash becomes publicized) to March 1, 1998 (when the region shows sign of recovery). we repeat the same estimation procedure, changing the turmoil period to:[16] (1) beginning from June 1, 1997 (the first crash of the Thai market); (2) beginning from August 7, 1997 (when the Indonesia and Thai markets plunged simultaneously); (3) ending on June 30, 1998 (the end of the second quarter); (4) ending on December 31, 1998.[17] In each case, the key results do not alter. In order to keep concise outputs, we only report partial results for each case.[18]

For the first set of the modified periods where the crisis is assumed to start on June 1, 1997, the estimates in Tables 19 and 20 show the similar results as we have seen in our benchmark analysis. First of all, there are only a few price spillovers occurred before the crisis (in this case only did Indonesia spill over to the Philippines, Thailand to Singapore, with which the coefficients are marginally significant). Second, the markets are strongly dependent on the past values of innovations and volatilities as indicated by significant coefficients of α_i and β_i. Third, the sample correlations during the turmoil period are higher than those for pre-crisis period. However, some differences in the results are observed. For example, there are more price spillover effects undergoing during the crisis, in particular, there is a feedback effect of shocks between the Philippines and Malaysia (Table 20). Moreover, less asymmetry coefficients are significant under sensible levels (only Indonesia and the Philippines are significant under the 5% and the 1% levels, respectively) in the pre-crash period (Table 19). This might due to less extreme observations in the series during the period when the Thai market first became volatile.

Modifying the crisis period to start on August 7, 1997 (Tables 21 and 22) does not change the central results we observed in the benchmark case, except that there are a few more price spillovers between markets in the pre-crash period, and then the effect disappears during the crisis period.

In the next two experiments, we extend the turmoil period to the end of the second quarter of 1998 (Tables 23 and 24) and the end of the same year (Tables 25 and 26), it seems that none of price spillover effects between the markets is significant under the 5% level (except for the results presented in Table 26 for the post-crash period, there are some observed price spillovers between markets), and the markets are not strongly sensitive to bad news. However, some conclusions derived from our benchmark analysis still hold: The news in the last period and the past volatilities have significant impacts on each market's current volatility. In addition, the degree of interdependence between the markets measured by sample correlation matrix is lower after the financial turmoil.

In sum, the significance of the price spillovers seems to vary with the different set of period definitions. It may be caused by some regime changing in the returns series. Specifically, the structural breaks exist when the markets go from tranquility to disturbance, and from economic turmoil to recovery. Also, the leverage effect becomes evident when one or two markets in the region start collapsing.

9. Conclusion

This paper uses an extended multivariate A-PGARCH model to investigate the dynamic transmission of five ASEAN stock markets for the period from the beginning of 1996 to the end of 1999. The investigation of price and volatility spillovers along with the leverage effects among these markets is motivated by the ongoing discussions on the Asian crisis literature, as well as the high level of economic integration between the ASEAN countries.

The results of the analysis suggest that an A-PGARCH model with a moving average returns can well describe the movements of the five ASEAN stock markets. There is evidence that the markets are strongly related to their own past values of innovations and volatilities, and significant linear dependencies in the market's returns could result from market inefficiencies or imperfect trading time among the markets. The market volatility seems to be time-varying with the asymmetric response of innovations like observed in Indonesia. The asymmetry in the reaction of the conditional volatility to the arrival of news, or the leverage effect, reflects that the market is likely to experience extreme up and down price movements when receiving bad news.

There are some directions to extend the study in this paper. First of all, a natural follow-up question is, do the markets really stabilize after experiencing the huge impact of a crisis like the one in Southeast Asia? In fact, although some markets in the Southeast Asia were in the course of recovery in the early 1998, the countries like Indonesia are still suffering from the social and economic turbulence periodically. Second, there might be some commonality of the shocks driving the market's volatility. In the paper by Engle and Susmel (1993), they propose a test to detect that the volatility of the stock markets share the same structure of driving forces. By applying the test, we will be able to investigate if the unexpected shocks of the market returns are idiosyncratic or result from the changes in global economic environments. Finally, the high degree of co-movements of stock markets during the periods of market stress may be caused by herd behavior of market participants. Insufficient provision of complete and accurate firm-specific information may be the main reason to suppress the investors' own beliefs to comply with "market consensus". Christie and Huang (1995) and Chang et al. (2000) have documented the presence of the herd behavior in the U.S. and the emerging markets by utilizing the cross-sectional standard deviation of returns and absolute deviation of returns, respectively. It would be fruitful to further investigate the nature of herding in the ASEAN markets and the extent of the impact on the financial markets during the Asian crisis.

FOOTNOTES

1. Among the other studies on the volatility transmission, Koutmos and Booth (1995) and Booth et al. (1997) use a Multivariate-EGARCH model to investigate the issue for New York, Tokyo and London stock markets, and the Scandinavian stock markets, respectively. Karoly (1995) applies a bivariate GARCH model for New York and Toronto stock markets.
2. This section draws heavily on the work of Forbes and Rigobon (1999a, 1999b), and Rigobon (1999).
3. See Masson (1998) for comprehensive survey on these mechanisms.
4. The overview of the ASEAN digests from the ASEAN official website at *http:// www.asean.or. id/history/ overview.htm*.
5. On March 1, 1998 several news headlines were written as follows: "Japan Expected To Unveil Fiscal-Stimulus Package By Mid-May", Dow Jones Online News; "Tokyo Stocks Open Up On Signs Of More Steps To Help Economy", Dow Jones International News; "South Korean Stocks Open Higher; Index Up 5.59 Pts To 564.57", Dow Jones International News; "Confidence Life To Provide Consolidation for Traders", South China Morning Post.
6. See the 1997–1998 ASEAN annual report. *http://www.asean.or.id/asc/r9798/ asc97v.htm*.
7. However, the standard deviation for Indonesia is about 0.78, next to the highest volatility among the markets, suggesting the market is somewhat volatile.
8. The complete results from the analysis are not listed here, but it is available from the author upon the request.
9. The sample size of the coverage periods is not enough to analyzed the seasonality issue during the crisis, thus the result is not available.
10. The stock indices under consideration are equally weighted, in the sense, the index gives more weight to the small firms. Moreover, Keim (1983) discovered that the large returns observed in January are primarily caused by small firms.
11. For the details on the properties and empirical applications of the ARCH or GARCH models, see Bollerslev et al. (1992) and (1994), Bera and Higgins (1993), and Palm (1996) for recent surveys.
12. For example, GJR model by Glosten, Jaganathan and Runkle (1993), Zakoian's (1994) TARCH

model , Bera and Higgins's (1993) NARCH model, and so on. For details, please refer to the appendix in Ding et al. (1993).

13. The conditional t-distribution allows for thicker tails than the normal distribution, and behaves as the normal distribution when the estimated degrees of freedom parameter (ν) go to infinity. On the other hand, for $4 < \nu < \infty$ the kurtosis coefficient of the t-distribution can be calculated by $3(\nu - 2)/(\nu - 4)$. Since the value is usually greater than 3, it suggests that the t-distribution can better account for the excess kurtosis in the unconditional distribution. See also Bera and Higgins (1993) and Bollerslev et al. (1994).
14. Bollerslev et al. (1992) suggest that $p = q = 1$ is the best combinations for most financial series.
15. Please see Appendix A for the detailed calculation.
16. The first two definitions are adopted from Forbes and Rigobon (1999a). For clarification, please see Figure 5 for graphic illustration of the partitioned periods.
17. Essentially we are assuming that the Southeast Asian markets are still vulnerable to the economic upheaval through the end of 1998 and starts its course of recovery after that.
18. Complete results can be requested from the author.

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Appendix A: Calculation of Volatility Spillovers

In order to demonstrate the calculation of volatility spillover parameters, we use two countries (country 1 and country 2) with $p = q = d = 1$ in the A-PGARCH model. Assume the stock returns for two countries ($R_{1,t}$ and $R_{2,t}$) have the following relationship,

$$R_{1,t} = c_1 + \phi_1 \epsilon_{1,t-1} + \epsilon_{1,t}$$

$$R_{2,t} = c_2 + \phi_2 \epsilon_{2,t-1} + \epsilon_{2,t}$$

Conditional innovations ($\epsilon_{i,t},\ i = 1, 2$) up to $t-1$ with t-distribution can be described as,

$$\begin{pmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \end{pmatrix} \Bigg| \Omega_{t-1} \sim t\ (0, H_t, \nu)$$

The covariance matrix of innovations, H_t, is written as follows:

$$H_t = \begin{bmatrix} \sigma_{1,t}^2 & \sigma_{12,t} \\ \sigma_{21,t} & \sigma_{2,t}^2 \end{bmatrix} = \begin{bmatrix} \sigma_{1,t} & 0 \\ 0 & \sigma_{2,t} \end{bmatrix} \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix} \begin{bmatrix} \sigma_{1,t} & 0 \\ 0 & \sigma_{2,t} \end{bmatrix} \tag{7}$$

where

$$\sigma_{1,t} = z_1 + \alpha_1(|\epsilon_{1,t-1}| + \gamma_1 \epsilon_{1,t-1}) + \beta_1 \sigma_{1,t-1} \tag{8a}$$

$$\sigma_{2,t} = z_2 + \alpha_2(|\epsilon_{2,t-1}| + \gamma_2 \epsilon_{2,t-1}) + \beta_2 \sigma_{2,t-1} \tag{8b}$$

The covariance between country 1 and country 2, $\sigma_{12,t}$ (or equivalently, $\sigma_{21,t}$), can be computed with equations (7), (8a) and (8b) assuming constant conditional correlations:

$$\begin{aligned} \sigma_{12,t} &= \rho \times \sigma_{1,t} \times \sigma_{2,t} \\ &= \rho \left[z_1 z_2 + \alpha_1 \alpha_2 (|\epsilon_{1,t-1}| + \gamma_1 \epsilon_{1,t-1})(|\epsilon_{2,t-1}| + \gamma_2 \epsilon_{2,t-1}) + \beta_1 \beta_2 \sigma_{1,t-1} \sigma_{2,t-1} \right] \end{aligned}$$

Thus, the volatility spillover parameters can be obtained by calculating $\rho \times \alpha_1 \times \alpha_2$.

Appendix B: Maximum Likelihood Estimation based on the Student t-distribution

The likelihood function with the Student t-distribution:

$$
\begin{aligned}
f_t(\theta) = &\left(\Gamma\left[(n+\nu)/2\right] \Big/ \left[\Gamma(\nu/2)\pi(\nu-2)^{n/2}\right]\right) \times |H_t|^{-1/2} \times \\
&\left[1 + (1/(\nu-2))\left(\epsilon_t' H_t^{-1} \epsilon_t\right)\right]^{-(n+\nu)/2}
\end{aligned} \tag{9}
$$

The model is estimated by maximizing the log-Likelihood function with Berndt-Hall-Hall-Hausman (1974) algorithm:

$$
l_t(\theta) = \log L(\theta) = \log\left[\Gamma(\frac{\nu+n}{2})\right] - \log\left[\Gamma(\frac{\nu}{2})\right] - \frac{1}{2}W \tag{10}
$$

where

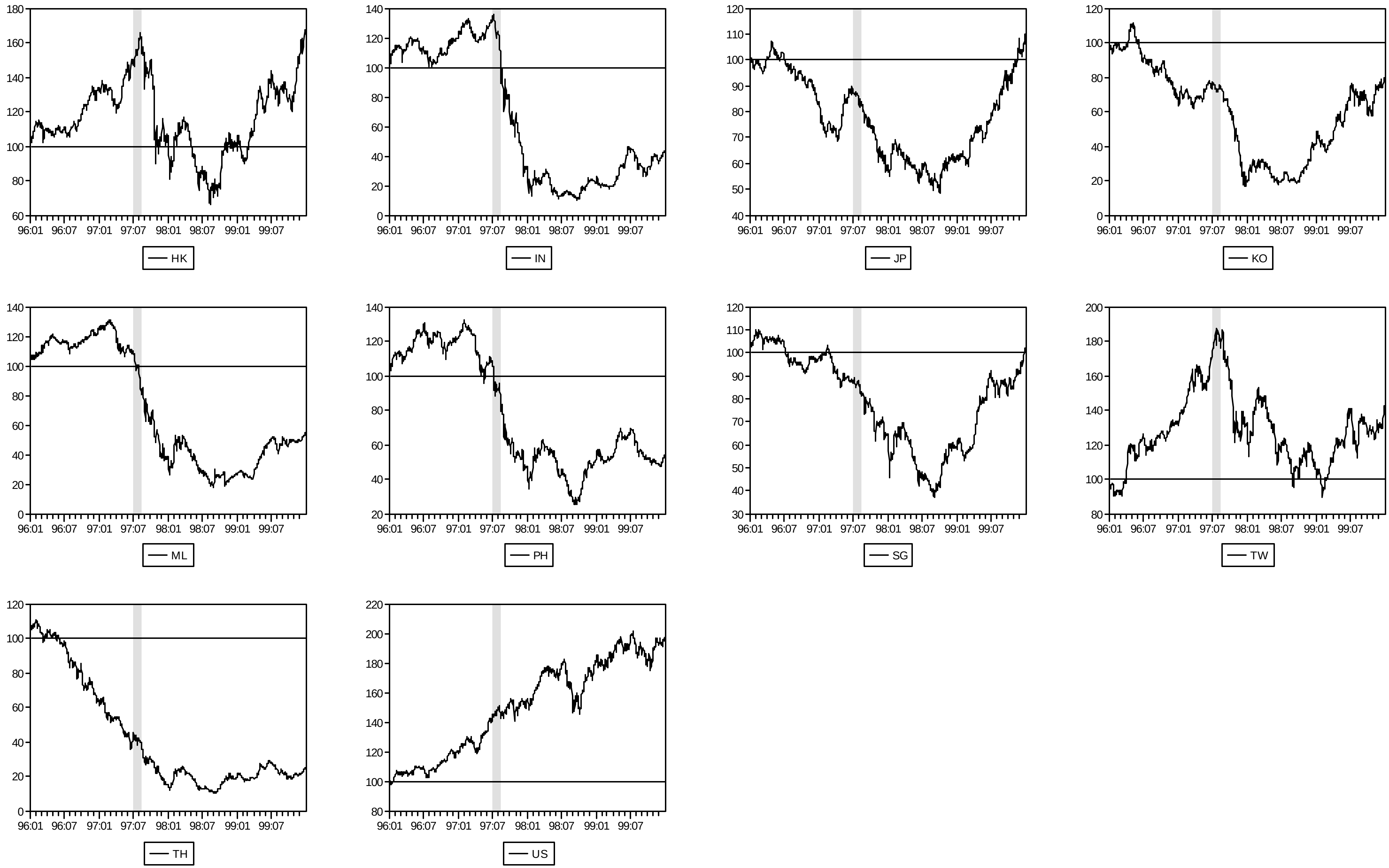
$$
W = \left[\log(|H_t|) + n\log\left((\nu-2)\pi\right) - \left(\frac{\nu+n}{2}\right)\log\left(1 + (\nu-2)^{-1}\epsilon_t' H_t^{-1}\epsilon_t\right)\right]
$$

and

$$
L(\theta) = \Pi_{t=1}^{T} f_t(\theta)
$$

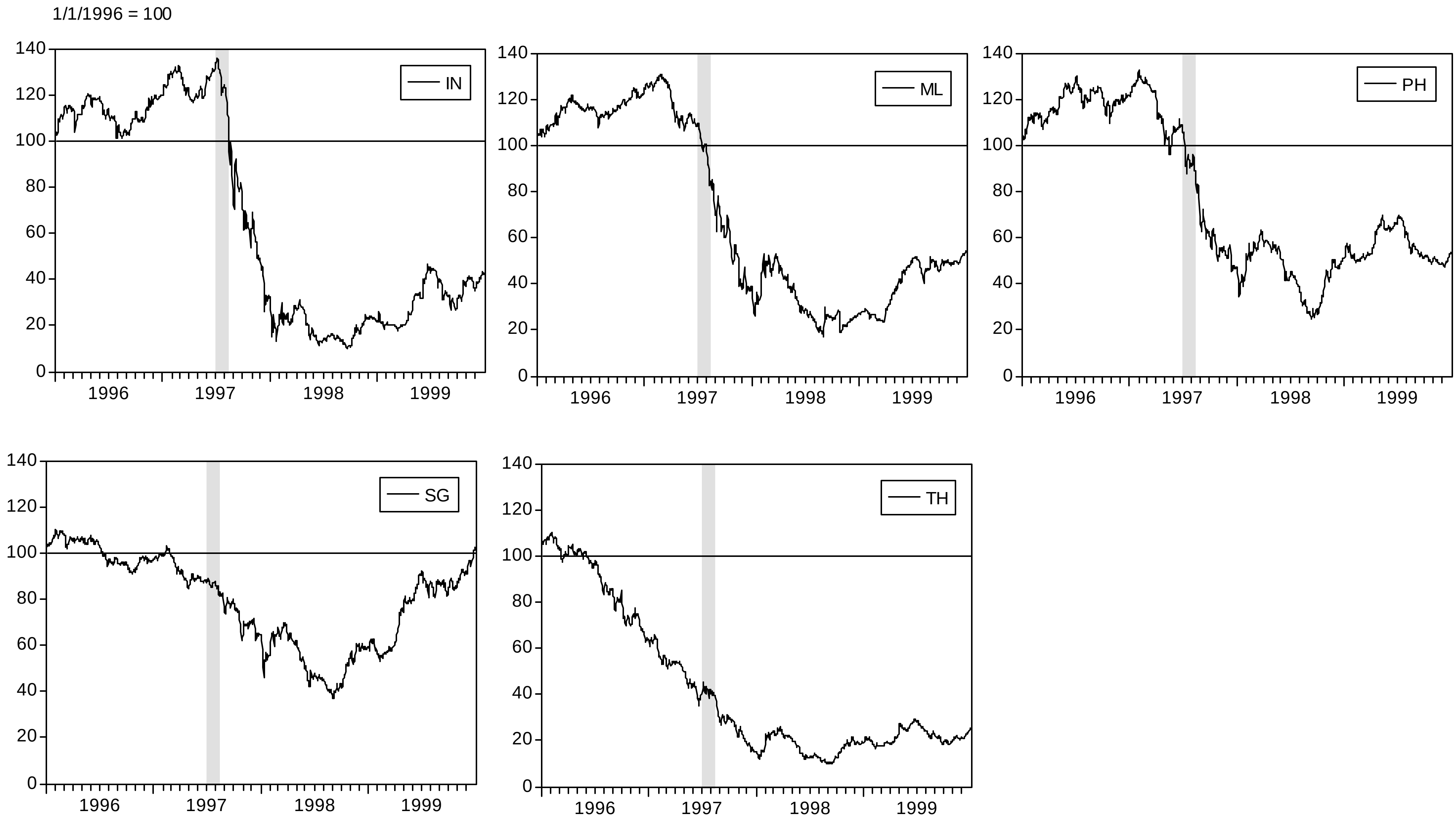
is the sample likelihood function. The number of the markets and the estimated parameters of the model are denoted by n and θ, respectively. S+GARCH developed by Insightful Corporation is used to estimate the model.

1/1/1996 = 100



Note: shaded area denotes the period of 7/1/97--7/31/97

Figure 1 Selected Stock Indices in US$



Note: shaded area denotes the period of 7/1/97--7/31/97

Figure 2 ASEAN Stock Indices in US$

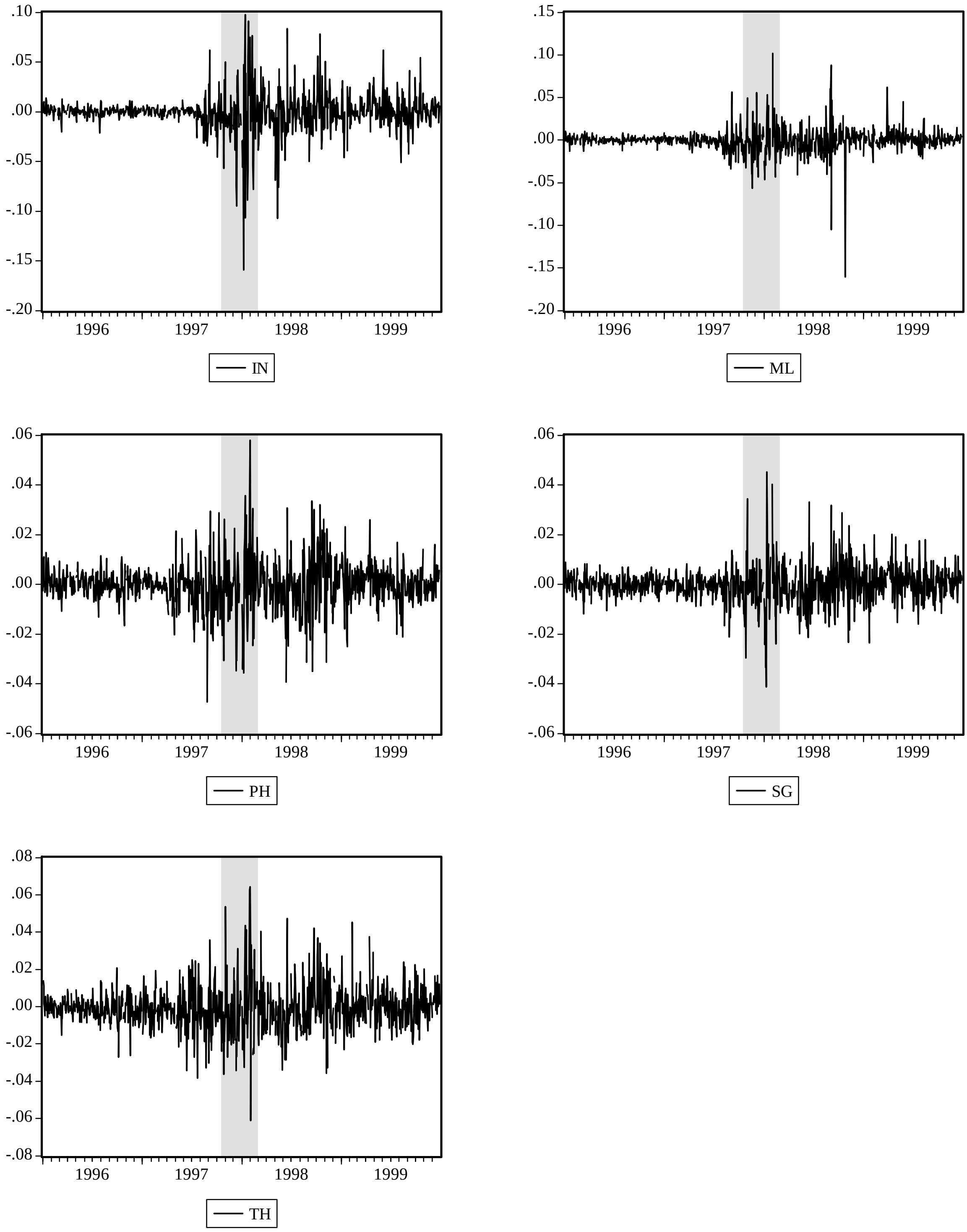


Figure 3 Daily Stock Returns
(shaded area: 10/17/97-3/1/98)

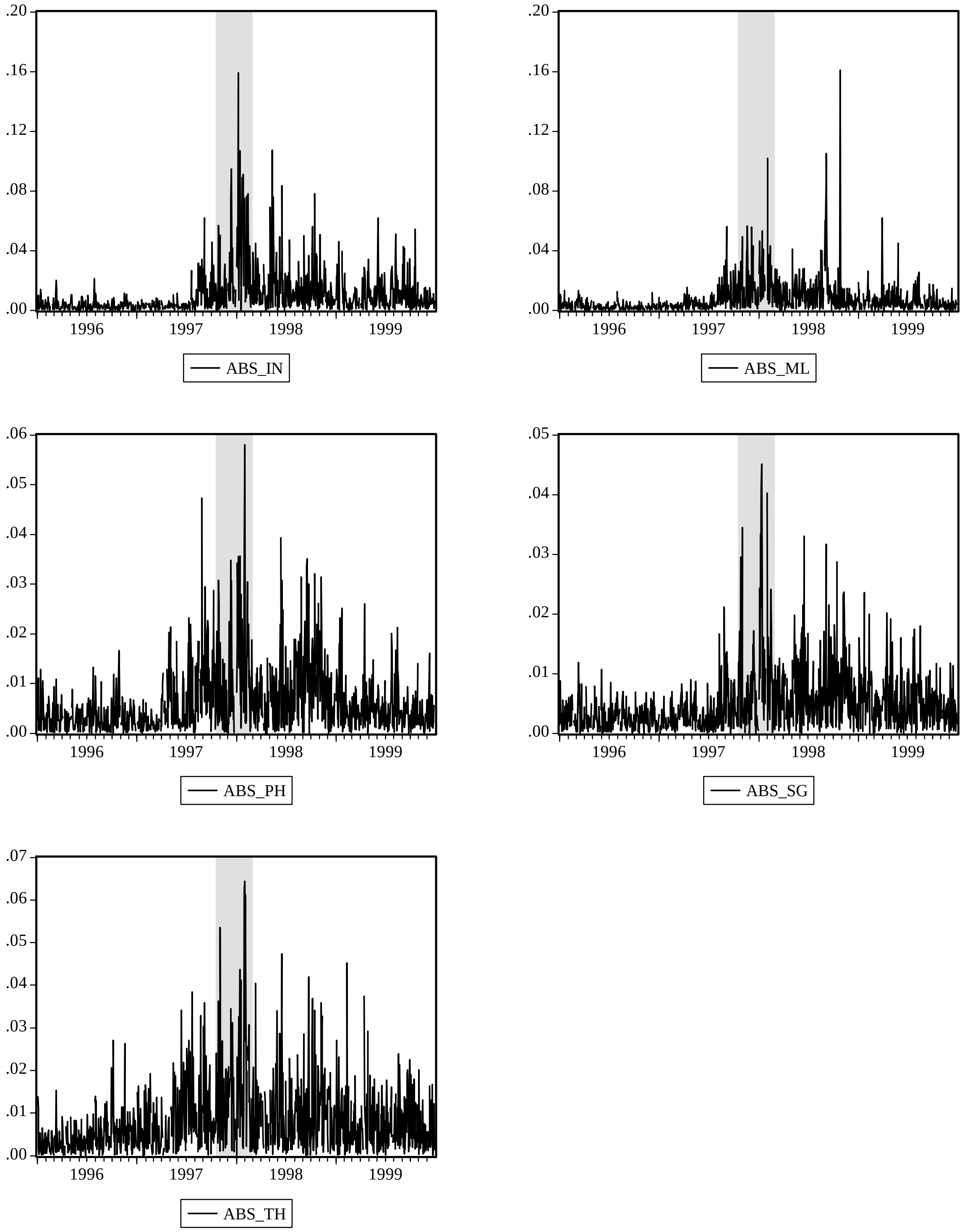


Figure 4 Daily Absolute Stock Returns
(shaded area: 10/17/97--3/1/98)

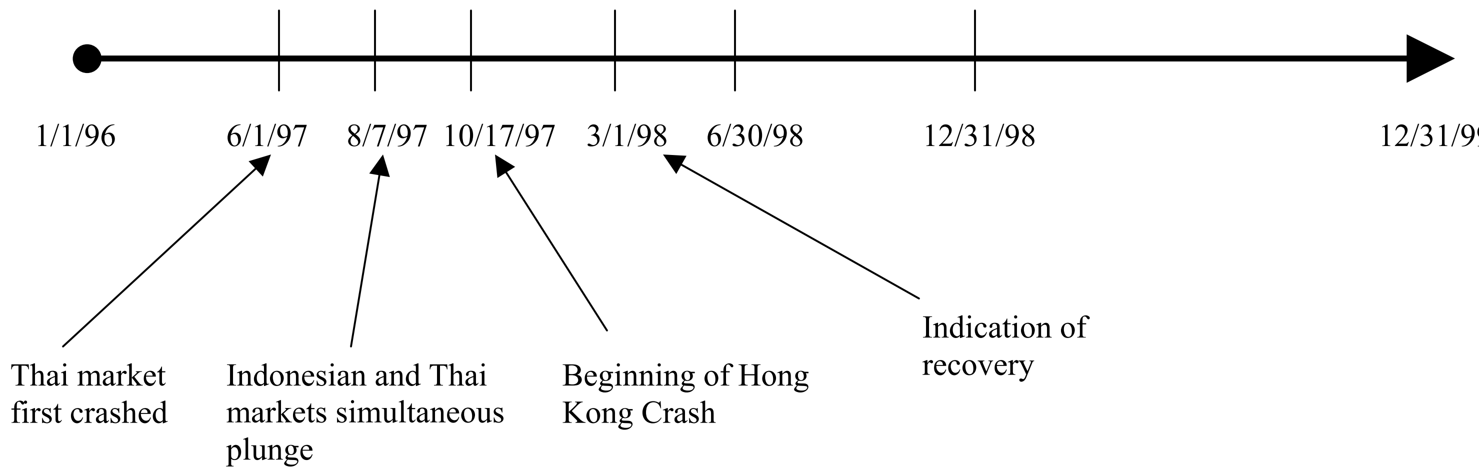


Figure 5 Definitions of Sub-Periods

Table 1 Market Value and Trading Volume in Selected Southeast Asian Markets
(currency in U.S.$ billons; end of period levels)

	1996	1997	1998	1999
Market Capitalization				
Indonesia	91	29	22	64
Malaysia	307	94	99	145
Philippines	81	31	35	48
Singapore	150	106	94	198
Thailand	100	24	35	58
Trading Value				
Indonesia	32	42	11	20
Malaysia	174	147	30	49
Philippines	26	20	10	19
Singapore	43	64	51	98
Thailand	44	23	22	42
Turnover ratio (%)				
Indonesia	40.7	64.2	59.4	47.0
Malaysia	65.1	72.6	30.9	39.8
Philippines	36.5	67.6	31.1	46.5
Singapore	28.7	49.9	50.5	66.9
Thailand	36.7	39.2	71.2	90.6
Number of Listed Companies				
Indonesia	253	282	287	277
Malaysia	621	708	736	757
Philippines	216	221	221	226
Singapore	223	303	321	355
Thailand	454	431	418	392

Source: Emerging Stock Markets Factbook, various volumes.

Table 2 Descriptions of Stock Market Indices

Market	Trading hours[1] Local time (New York time)	Index	Details of the index construction[2]
Indonesia	10:00 – 12:00 (22:00 – 12:00)	Jakarta Composite	Capitalization-weighted price index, the index is computed based on Paäsche formula (the current-year method)[3].
Malaysia	10:00 – 11:00 11:15 – 12:30 14:30 –16:00 (21:00 – 22:00 22:15 – 23:30 01:30 – 03:00)	KLSE Composite	Capitalization-weighted price index, the index is computed based on Laspeyres formula (the base-year method).
Philippines	9:30 – 12:15 (20:30 – 23:15)	PSE Composite	Capitalization-weighted price index, the index is computed based on Paäsche formula with daily changes.
Singapore	10:00 – 12:30 14:30 – 16:00 (21:00 – 23:30 01:30 – 03:00)	SES All-Singapore	Capitalization-weighted price index, the index is computed based on Lasperyres formula.
Thailand	08:30 – 17:00 (20:30 – 05:00)	SET	Capitalization-weighted price index, the index is computed based on Paäsche formula.

Source:

1. Sheng and Tu (2000), Table 5.
2. World Stock Exchange Fact Book (1998).
3. For details on the computation methods, please refer to the appendix of World Stock Exchange Fact Book (1998).

Table 3 Descriptive Statistics of Stock Returns: Full Sample (1/1/1996 to 12/31/1999)

	Indonesia	**Malaysia**	**Philippines**	**Singapore**	**Thailand**
Mean[a]	-0.0474	-0.0342	-0.0268	0.0014	-0.0666
Median [a]	-0.0050	-0.0254	-0.0113	0.0169	-0.1235
S.D.[a]	1.7907	1.3547	0.9309	0.7170	1.1799
Skewness	-0.9444	-1.0394	1.5763	0.3033	0.6755
Kurtosis	17.08	33.38	7.29	8.87	7.14
JB[b,c]	8321.17*	38300.82*	761.47*	1457.38*	777.13*
Q(12)[d]	89.86*	35.65*	110.51*	35.54*	49.06*
$Q^2(12)$[e]	404.09*	43.35*	339.19*	337.08*	308.66*
PP[f]	-26.60*	-29.85*	-23.06*	-26.55*	-25.49*
Obs.	990	991	995	1006	982

Note: a. The values are multiplied by 100
b. Jarque-Bera Statistics
c. * significant at 5%; ** significant at 10%
d. Q(*k*): the Ljung-Box Q-statistics for standardized residuals at lag *k*
e. $Q^2(k)$: the Ljung-Box Q-statistics for square standardized residuals at lag *k*
f. PP: Phillips-Perron Unit Root Test Statistics

Table 4 Descriptive Statistics of Stock Returns: Stability Period I (1/1/1996 to 10/16/1997)

	Indonesia	**Malaysia**	**Philippines**	**Singapore**	**Thailand**
Mean	-0.0471	-0.0415	-0.0475	-0.0275	-0.1253
Median	0.0051	-0.0178	-0.0216	0.0058	-0.1351
S.D.	0.7786	0.6704	0.6950	0.3904	0.8654
Skewness	-0.1156	0.9939	-0.5618	-0.4782	-0.1490
Kurtosis	17.44	19.22	9.64	5.68	5.89
JB	3868.99*	4953.16*	843.62*	152.49*	155.55*
Q(12)	175.76*	61.95*	71.36*	33.02*	34.87*
$Q^2(12)$	194.54*	196.78*	152.27*	95.79*	148.53*
PP	-13.08*	-16.32*	-15.33*	-17.89*	-17.66*
Obs.	445	445	446	451	442

Table 5 Descriptive Statistics of Stock Returns: Turmoil Period (10/17/1997 to 3/1/1998)

	Indonesia	**Malaysia**	**Philippines**	**Singapore**	**Thailand**
Mean	-0.5498	-0.1449	-0.0311	-0.0475	-0.0958
Median	-0.4585	-0.3677	-0.0377	-0.0112	-0.3386
S.D.	4.0385	2.4821	1.6371	1.3358	2.1173
Skewness	-0.5275	0.9002	0.3638	0.2880	0.6731
Kurtosis	5.28	5.48	4.13	5.35	4.34
JB	23.33*	34.42*	6.88*	22.21*	13.57*
Q(12)	17.57	11.27	27.28*	9.60	8.49
$Q^2(12)$	17.05	2.72	9.31	25.04*	22.73*
PP	-8.54*	-8.61*	-6.16*	-8.25*	-7.19*
Obs.	89	88	91	91	90

Table 6 Descriptive Statistics of Stock Returns: Stability Period II (3/2/1998 to 12/31/1999)

	Indonesia	**Malaysia**	**Philippines**	**Singapore**	**Thailand**
Mean	0.0503	-0.0057	-0.0058	0.0391	-0.0032
Median	0.0218	-0.0073	0.0152	0.0382	-0.0813
S.D.	1.7792	1.5371	0.9411	0.7863	1.1873
Skewness	-0.2129	-2.2859	-0.1457	0.2704	0.7160
Kurtosis	8.88	36.34	5.00	4.38*	4.86
JB	660.67*	21610.37*	78.01*	42.41*	103.17*
Q(12)	32.91*	12.50	36.31*	20.07**	29.56*
$Q^2(12)$	36.91*	15.63	151.66*	64.77*	25.11*
PP	-17.99*	-21.34*	-17.12*	-17.72*	-17.65*
Obs.	456	458	458	464	450

Table 7 Returns by Day of the Week: Stability Period I (1/1/1996 to 10/16/1997)

	Highest Mean	**Lowest Mean**	**Highest SD**	**Lowest SD**
Indonesia	Wednesday	Monday	Friday	Tuesday
Malaysia	Friday	Monday[**]	Wednesday	Tuesday
Philippines	Friday	Monday[**]/Tuesday[**]	Thursday	Wednesday
Singapore	Friday	Monday[*]	Monday	Tuesday
Thailand[a]	Thursday	Monday[*]	Monday	Tuesday

Note: 1. 'a' denotes The difference of returns across the days is significant at 10%.
2. [*] significant at 5%; [**] significant at 10%.

Table 8 Returns by Day of the Week: Turmoil Period (10/17/1997 to 3/1/1998)

	Highest Mean	**Lowest Mean**	**Highest SD**	**Lowest SD**
Indonesia	Wednesday	Thursday	Thursday	Wednesday
Malaysia	Tuesday	Thursday	Tuesday	Friday
Philippines	Wednesday	Thursday[**]	Monday	Thursday
Singapore	Wednesday	Thursday	Monday	Friday
Thailand	Wednesday	Monday	Monday	Friday

Note: [*] significant at 5%; [**] significant at 10%.

Table 9 Returns by Day of the Week: Stability Period II (3/2/1998 to 12/31/1999)

	Highest Mean	**Lowest Mean**	**Highest SD**	**Lowest SD**
Indonesia	Friday[**]	Wednesday[**]	Wednesday	Tuesday
Malaysia	Friday	Monday	Wednesday	Thursday
Philippines	Thursday	Friday	Monday	Tuesday
Singapore[a]	Wednesday	Monday	Monday	Tuesday
Thailand[a]	Friday	Monday[*]	Wednesday	Tuesday

Note: 1. 'a' denotes The difference of returns across the days is significant at 10%.
2. [*] significant at 5%; [**] significant at 10%.

Table.10 Stock Returns by Months: Stability Period I (1/1/1996 to 10/16/1997)

	Highest Mean	Lowest Mean	Highest SD	Lowest SD
Indonesia[b]	January*/November**	August**/October/July**	August	January
Malaysia[b]	November*/February*	August/July*	September	November
Philippines[b]	January*	August/July**/April**	August	January
Singapore[b]	January*	Oct**/Mar**/Aug/Jul**/Apr/Jun*	August	June
Thailand	November	Aug/Oct**/Dec*	August	April

Note: 1. 'b' denotes The difference of returns across the days is significant at 5%.
2. * significant at 5%; ** significant at 10%.

Table.11 Returns by Months: Stability Period II (3/2/1998 to 12/31/1999)

	Highest Mean	Lowest Mean	Highest SD	Lowest SD
Indonesia	October*	August	January	February
Malaysia[b]	December*/November**	August	October	December
Philippines	October**	August*	January	February
Singapore	October**	August	January	December
Thailand	October*	August**/May*	January	December

Note: 1. 'b' denotes The difference of returns across the days is significant at 5%.
2. * significant at 5%; ** significant at 10%.

Table 12 Results of Univariate PGARCH: Stability Period I (1/1/1996 ~ 10/16/1997)

Country	IN	ML	PH	SG	TH
MEAN					
DAY(coef.)[s.e.]	MON* (0.1125)[0.0454] WED* (0.0926)[0.0395] FRI* (0.1113)[0.0439]	MON** (-0.0615)[0.0386]	TUE* (-0.0866)[0.0427] FRI (0.0403)[0.0443]	MON* (-0.0793)[0.0410]	MON* (-0.2083)[0.0653]
MONTH	JAN* (0.1601)[0.0728] NOV* (0.2528)[0.0981]	JUL* (-0.0785)[0.0437] NOV (0.0834)[0.0662]	JAN* (0.1866)[0.0669] MAY* (0.1677)[0.0837] JUL** (-0.1087)[0.0715]	JAN* (0.1122)[0.0527] MAY* (0.1077)[0.0561] NOV** (0.1244)[0.0768]	JUL* (-0.1626)[0.0855] OCT* (-0.2769)[0.1013] NOV** (0.2096)[0.1553]
HOLIDAY	** (-0.1339)[0.0888]	Pr>10%	Pr>10%	Pr>10%	Pr>10%
VARIANCE					
ARCH(coef.)[s.e.]	ARCH(1)* (0.1014)[0.0393]	ARCH(1)*(0.0688)[0.0281]	ARCH(1)* (0.0585)[0.0254]	ARCH(1)* (0.0849)[0.0395]	ARCH(1)* (0.0734)[0.0287]
GARCH	GARCH(1)* (0.8653) [0.0369]	GARCH(1)* (0.9177) [0.0272]	GARCH(1)* (0.9285) [0.0235]	GARCH(1)* (0.8368) [0.0603]	GARCH(1)* (0.9313) [0.0249]
LEVERAGE	LEV(1)* (-0.9999)[0.4949]	LEV(1)* (-0.9999)[0.5091]	LEV(1)* (-0.9999)[0.5964]	LEV(1) (-0.3977)[0.3202]	LEV(1)* (-0.9600)[0.3867]
DAY		THU* (-0.0864)[0.0481] FRI** (0.0643)[0.0432]		TUE* (-0.1087)[0.0478] FRI** (-0.0610)[0.0455]	WED* (0.1706)[0.0888]
MONTH	DEC* (-0.0222)[0.0161]		JAN* (-0.0108)[0.0060]	AUG* (0.0313)[0.0149]	NOV* (0.0293)[0.0163]
HOLIDAY	Pr>10%	Pr>10%	Pr>10%	Pr>10%	Pr>10%
USTB3M	Pr>10%	Pr>10%	Pr>10%	Pr>10%	Pr>10%
ν	6.07	11.59	12.78	16.35	5.19
L-B(12) (P-value)	16.91 (0.1531)	6.048 (0.9137)	17.32 (0.1379)	15.42 (0.2191)	11.83 (0.4592)
L-B^2(12) (P-value)	8.865 (0.7144)	4.561 (0.9711)	17.79 (0.1221)	12.33 (0.4199)	6.4999 (0.8889)
LM(12) (P-value)	9.105 (0.694)	4.531 (0.9718)	15.34 (0.2234)	11.88 (0.455)	6.702 (0.8767)

Note:

a. L-B statistic: Ljung-Box test statistic for standardized residuals

b. L-B^2: Ljung-Box test statistic for squared standardized residuals

c. LM: Lagrange Multiplier test statistic

d. * significant at 5%; ** significant at 10%

e. Estimated coefficients are in round parentheses ( ) and standard errors are in square brackets [ ].

Table 13 Results of Univariate PGARCH: Turmoil Period (10/17/1997 ~ 3/1/1998)

	IN	ML	PH	SG	TH
MEAN					
DAY	MON (0.6737)[0.7742]	MON (-0.2946)[0.5181]	WED* (0.5583)[0.2897]		WED* (0.6337)[0.2860]
MONTH					
HOLIDAY	Pr>10%	Pr>10%	Pr>10%		Pr>10%
VARIANCE					
ARCH	ARCH(1)** (0.1084)[0.0664]	ARCH(1)* (0.3444)[0.1248]	ARCH(1) (0.1163)[0.1181]	ARCH(1) (0.1528)[0.1226]	ARCH(1) (0.1698)[0.1342]
GARCH	GARCH(1)* (0.8620) [0.0846]	GARCH(1)* (0.5169) [0.2004]	GARCH(1) (0.4281) [0.3508]	GARCH(1)* (0.7887) [0.1450]	GARCH(1)* (0.5082) [0.2705]
LEVERAGE	LEV(1) (-0.9999)[0.9409]	LEV(1) (-0.0569)[0.2087]	LEV(1) (0.5905)[0.8804]	LEV(1)** (-0.9999)[0.7692]	LEV(1) (0.8124)[0.6773]
DAY		TUE** (1.1554)[0.8733] WED* (-1.3697)[0.6644]			TUE (0.5328)[0.4997] WED* (-1.1111)[0.4361]
MONTH					
HOLIDAY	Pr>10%	** (1.4667)[1.1200]	Pr>10%		Pr>10%
USTB3M	Pr>10%	Pr>10%	* (-2.5166)		* (-1.7769) [0.9170]
ν	10.57	9.99	11.03	6.91	13.87
L-B(12) (P-value)	8.062 (0.7803)	11.59 (0.4795)	10.48 (0.5737)	5.574 (0.936)	4.509 (0.9724)
L-B^2(12) (P-value)	12.16 (0.4327)	12.64 (0.3954)	11.75 (0.4658)	7.984 (0.7864)	9.115 (0.6931)
LM(12) (P-value)	7.501 (0.8228)	9.457 (0.6634)	9.809 (0.6327)	6.11 (0.9104)	8.933 (0.7086)

Note:

a. L-B statistic: Ljung-Box test statistic for standardized residuals

b. L-B^2: Ljung-Box test statistic for squared standardized residuals

c. LM: Lagrange Multiplier test statistic

d. * significant at 5%; ** significant at 10%

e. Estimated coefficients are in round parentheses ( ) and standard errors are in square brackets [ ].

f. Since none of the day-of-the-week variables are significant under 5% or 10% level in the case of Singapore, the estimates presented are from model A.

Table 14 Results of Univariate PGARCH: Stability Period II (3/2/1998 ~ 12/31/1999)

	IN	ML	PH	SG	TH
MEAN					
DAY		FRI* (0.1760)[0.0744]		MON* (-0.1931)[0.0747] TUE* (-0.1651)[0.0817]	MON** (-0.2010)[0.1265]
MONTH		APR*(0.3080)[0.1301] MAY(0.1998)[0.1734] SEP* (-0.3202)[0.1210] DEC* (0.2142)[0.0910]	AUG* (-0.3062)[0.1503] DEC* (0.3094)[0.1079]	MAY* (-0.2389)[0.1155] JUL* (-0.1960)[0.1107] AUG* (-0.3242)[0.1186]	MAY* (-0.4888)[0.1956] AUG* (-0.4567)[0.1760] OCT** (0.3726)[0.2276]
HOLIDAY	Pr>10%	** (-0.3249)[0.2312]	Pr>10%	Pr>10%	* (0.3360)[0.1906]
VARIANCE					
ARCH	ARCH(1)**(0.0392)[0.0284]	ARCH(1)* (0.1274)[0.0391]	ARCH(1)* (0.1703)[0.0352]	ARCH(1)* (0.1232)[0.0457]	ARCH(1) (0.0185)[0.0201]
GARCH	GARCH(1)*(0.9268) [0.0341]	GARCH(1)* (0.8644) [0.0378]	GARCH(1) * (0.8254) [0.0384]	GARCH(1)* (0.8265) [0.0603]	GARCH(1)* (0.9755) [0.0308]
LEVERAGE	LEV(1) (-0.9999)[0.8141]	LEV(1)* (-0.6397)[0.2003]	LEV(1)** (-0.2056)[0.1275]	LEV(1)* (-0.5603)[0.2426]	LEV(1) (-0.0246)[0.7521]
DAY		THU* (-0.2983)[0.1453]	TUE* (-0.2576)[0.0837] FRI* (-0.2665)[0.1075]	WED** (0.1281)[0.0976] THU** (-0.1427)[0.0917]	MON* (0.3694)[0.1250] WED* (0.3179)[0.1256]
MONTH	FEB* (-0.1194)[0.0230]	MAY** (0.0561)[0.0418] NOV** (-0.0321)[0.0210]	DEC* (-0.0404)[0.0233]		SEP** (0.0296)[0.0182] NOV* (-0.0233)[0.0115]
HOLIDAY	Pr>10%	* (0.2780)[0.1331]	** (0.1925)[0.1292]	Pr>10%	** (0.1268)[0.0930]
USTB3M	* (-0.0568)[0.0219]	Pr>10%	Pr>10%	* (-0.0454)[0.0184]	Pr>10%
ν	4.39	3.29	24.79	34.33	6.03
L-B(12) (P-value)	14.95 (0.2440)	7.624 (0.8138)	11.08 (0.5221)	9.777 (0.6355)	10 (0.6159)
L-B^2(12) (P-value)	16.26 (0.1795)	0.4465 (>0.9999)	12.66 (0.3945)	10.41 (0.5803)	8.413 (0.7521)
LM(12) (P-value)	16.98 (0.1505)	0.4335 (>0.9999)	12.88 (0.3780)	9.615 (0.6497)	9.894 (0.6253)

Note:

a. L-B statistic: Ljung-Box test statistic for standardized residuals

b. L-B^2: Ljung-Box test statistic for squared standardized residuals

c. LM: Lagrange Multiplier test statistic

d. * significant at 5%; ** significant at 10%

e. Estimated coefficients are in round parentheses ( ) and standard errors are in square brackets [ ].

Table 15 Model Specification Comparisons[a]

Model A: the basic A-PGARCH(1,1,1) model with MA(1) without seasonal dummies, holiday dummy and interest rates

$$R_{i,t} = \phi_{i0} + \lambda_i \varepsilon_{i,t-1} + \varepsilon_{i,t} \quad \text{for } i = 1,\dots,5$$

$$\sigma_{i,t} = \alpha_{i0} + \alpha_{i1}(|\varepsilon_{i,t-1}| + \gamma_i \varepsilon_{i,t-1}) + \alpha_{i2}\sigma_{i,t-1} \quad \text{for } i = 1,\dots,5$$

Model B: Model A with holiday dummy and interest rates

$$R_{i,t} = \phi_{i0} + \phi_{i1} HOL_{i,t} + \lambda_i \varepsilon_{i,t-1} + \varepsilon_{i,t} \quad \text{for } i = 1,\dots,5$$

$$\sigma_{i,t} = \alpha_{i0} + \alpha_{i1}(|\varepsilon_{i,t-1}| + \gamma_i \varepsilon_{i,t-1}) + \alpha_{i2}\sigma_{i,t-1} + \alpha_{i3} HOL_{i,t} + \alpha_{i4} USTB3M_{i,t} \quad \text{for } i = 1,\dots,5$$

Model C: Model B with seasonal dummies

$$R_{i,t} = \phi_{i0} + \phi_{i1} HOL_{i,t} + \sum_{d=1}^{7} \zeta_{id} DAY_{i,t} + \sum_{m=1}^{12} \eta_{im} MONTH_{i,t} + \lambda_i \varepsilon_{i,t-1} + \varepsilon_{i,t} \quad \text{for } i = 1,\dots,5$$

$$\sigma_{i,t} = \alpha_{i0} + \alpha_{i1}(|\varepsilon_{i,t-1}| + \gamma_i \varepsilon_{i,t-1}) + \alpha_{i2}\sigma_{i,t-1} + \alpha_{i3} HOL_{i,t} + \sum_{d=1}^{7} \beta_{id} DAY_{i,t} + \sum_{m=1}^{12} \delta_{im} MONTH_{i,t} + \alpha_{i4} USTB3M_{i,t} \quad \text{for } i = 1,\dots,5$$

where

$HOL_{i,t}$ = 1 if the first trading day after a holiday; = 0 otherwise. $DAY_{i,t}$ = the-day-of-week dummies

$MONTH_{i,t}$ = the monthly dummies $USTB3M_{i,t}$ = the 3-month U.S. treasury bill rates

Stability Period I

	IN			ML			PH			SG			TH		
Model	A	B	C	A	B	C	A	B[b]	C	A	B	C	A	B	C
AIC	615.8	620.4	**609.7**	**526.9**	549.5	529.7	**664.6**	702.7	665.8	379.5	384.4	**376.4**	974.1	978.2	**969.1**
BIC	**648.6**	665.5	679.4	**555.5**	590.4	591.1	**693.3**	743.7	731.4	**408.3**	425.5	446.3	**1002.7**	1019.1	1034.6

Turmoil Period

	IN			ML			PH			SG			TH		
Model	A	B	C	A	B	C	A	B	C	A	B	C	A	B	C
AIC	**477.0**	477.6	477.1	412.6	411.9	**408.2**	**337.1**	346.6	342.8	**287.8**	298.3	NA	385.4	385.6	**380.5**
BIC	**494.4**	502.5	504.5	**430.0**	436.6	440.4	**354.7**	371.7	370.4	**305.4**	323.4	NA	**402.9**	410.6	413.0

Stability Period II

	IN			ML			PH			SG		
Model	A	B	C	A	B	C	A	B	C	A	B	C
AIC	1678.1	1678.4	**1664.4**	1332.9	1329.9	**1317.2**	1105.9	1108	**1097.7**	1042.7	1039.0	**1027.8**
BIC	**1707.0**	1719.7	1709.7	**1361.8**	1371.1	1391.5	**1134.7**	1149	1159.6	**1071.7**	1080.4	1098.2

	TH		
AIC	1396.5	1398.3	**1376**
BIC	**1425.3**	1439.4	1450

Note: a. the numbers in bold are the lowest values of the model selection criterion based on a model specification.
b. the specifications fail the Ljung-Box tests.

Table 16 Results of the Multivariate PGARCH[a]: Stability Period I (1/1/1996 ~ 10/16/1997)

Obs. = 469	IN ($i = 1$)	ML ($i = 2$)	PH ($i = 3$)	SG ($i = 4$)	TH ($i = 5$)
Price spillover parameters					
ϕ_{i1} (IN)	0.1440[*b]	0.0445	0.0865[*]	0.0201	-0.0547
	(0.0539)	(0.0429)	(0.0432)	(0.0261)	(0.0506)
ϕ_{i2} (ML)	0.0553	0.0513	0.0279	0.0227	0.0068
	(0.0510)	(0.0570)	(0.0448)	(0.0303)	(0.0651)
ϕ_{i3} (PH)	-0.0456	0.0028	-0.0037	0.0011	0.0038
	(0.0424)	(0.0414)	(0.0415)	(0.0270)	(0.0554)
ϕ_{i4} (SG)	-0.0185	0.0167	0.0419	0.0215	0.0650
	(0.0741)	(0.0709)	(0.0619)	(0.0457)	(0.0889)
ϕ_{i5} (TH)	0.0094	0.0042	-0.0028	0.0140	0.0208
	(0.0266)	(0.0274)	(0.0247)	(0.0167)	(0.0440)
Volatility spillover parameters					
α_i	0.0683[*]	0.0750[*]	0.0566[*]	0.0975[*]	0.0753[*]
	(0.0210)	(0.0300)	(0.0174)	(0.0257)	(0.0177)
α_{i2}[c]	0.0024				
α_{i3}	0.0018	0.0013			
α_{i4}	0.0028	0.0037	0.0021		
α_{i5}	0.0012	0.0013	0.0006	0.0018	
Other parameters					
β_i	0.8680[*]	0.8836[*]	0.9024[*]	0.8463[*]	0.8877[*]
	(0.0257)	(0.0329)	(0.0221)	(0.0437)	(0.0270)
γ_i	-0.9999[*]	-0.7802[*]	-0.6567[*]	-0.2647[*]	-0.3249[*]
	(0.3690)	(0.3328)	(0.3089)	(0.1362)	(0.1313)
ρ_{i2}[d]	0.4630				
ρ_{i3}	0.4672	0.3055			
ρ_{i4}	0.4238	0.5099	0.3802		
ρ_{i5}	0.2335	0.2375	0.1369	0.2418	
ν[e]	32.00				

Note:

a. see Eqs. (1)-(4) and constants in the mean and variance equations are not listed here.

b. [*] significant at 5%, [**] significant at 10% and the numbers in parentheses denote the standard error for the estimated coefficients.

c. see appendix for calculation of parameters of the volatility spillover.

d. we assume the sample correlations and the conditional correlations are the same to reduce the burden of computation with the number of observations in each period and a substantial amount of the parameters of the model.

e. if $\nu > 4$ or $1/\nu < 0.25$, then using the Student-*t* distribution is appropriate. For details, see Baillie and Bollerslev (1995)

Table 17 Results of the Multivariate PGARCH: Turmoil Period (10/17/1997 ~ 3/1/1998)

Obs. = 96	IN (i = 1)	ML (i = 2)	PH (i = 3)	SG (i = 4)	TH (i = 5)
Price spillover parameters					
ϕ_{i1} (IN)	0.0833	0.0596	0.0562	-0.0098	0.0507
	(0.1634)	(0.1128)	(0.0704)	(0.0489)	(0.0802)
ϕ_{i2} (ML)	-0.1516	-0.1417	-0.0795	-0.0952	-0.1581
	(0.1777)	(0.1503)	(0.1017)	(0.0879)	(0.1611)
ϕ_{i3} (PH)	0.2260	0.1413	-0.0946	-0.0183	-0.0589
	(0.3674)	(0.2548)	(0.2071)	(0.1616)	(0.2715)
ϕ_{i4} (SG)	-0.5178	0.3574	0.0440	0.1110	0.1609
	(0.4153)	(0.4717)	(0.2367)	(0.1525)	(0.2886)
ϕ_{i5} (TH)	0.1765	-0.0180	0.1585**	0.0776	0.1755
	(0.3002)	(0.2241)	(0.1124)	(0.1051)	(0.2076)
Volatility spillover parameters					
α_i	0.1395*	-0.0030	0.1720	0.0413	0.0033
	(0.0599)	(0.0885)	(0.1412)	(0.0391)	(0.0577)
α_{i2}	-0.0002				
α_{i3}	0.0123	-0.0003			
α_{i4}	0.0035	-0.0001	0.0045		
α_{i5}	0.0002	<-0.0000	0.0004	0.0001	
Other parameters					
β_i	0.7797*	0.4922	0.6281*	0.9382*	0.9445*
	(0.1197)	(2.8627)	(0.2776)	(0.1096)	(0.1332)
γ_i	-0.4071	0.7069	0.0048	-0.9999	0.9999
	(0.3808)	(21.6527)	(0.3542)	(1.2965)	(28.1038)
ρ_{i2}	0.4963				
ρ_{i3}	0.5140	0.5015			
ρ_{i4}	0.6049	0.6272	0.6339		
ρ_{i5}	0.4080	0.5489	0.6331	0.5777	
ν	27.05				

Table 18 Results of the Multivariate PGARCH: Stability Period II (3/2/1998 ~ 12/31/1999)

Obs. = 480	IN (i = 1)	ML (i = 2)	PH (i = 3)	SG (i = 4)	TH (i = 5)
Price spillover parameters					
ϕ_{i1} (IN)	0.1096*	-0.0268	0.0176	0.0008	0.0043
	(0.0580)	(0.0428)	(0.0204)	(0.0206)	(0.0331)
ϕ_{i2} (ML)	-0.0239	0.0403	0.0272	0.0619*	0.0132
	(0.0670)	(0.0417)	(0.0237)	(0.0237)	(0.0429)
ϕ_{i3} (PH)	-0.0621	0.1171**	0.1189*	0.0307	0.0601
	(0.1048)	(0.0901)	(0.0525)	(0.0385)	(0.0678)
ϕ_{i4} (SG)	0.0195	0.0283	0.1924*	0.0481	0.2882*
	(0.1184)	(0.1058)	(0.0594)	(0.0572)	(0.0814)
ϕ_{i5} (TH)	0.2084*	-0.0648	0.0295	0.0342	-0.0172
	(0.0897)	(0.0713)	(0.0371)	(0.0350)	(0.0603)
Volatility spillover parameters					
α_i	0.0930*	0.0317*	0.1594*	0.0855*	0.0535*
	(0.0249)	(0.0031)	(0.0353)	(0.0328)	(0.0235)
α_{i2}	0.0008				
α_{i3}	0.0058	0.0009			
α_{i4}	0.0031	0.0008	0.0062		
α_{i5}	0.0021	0.0004	0.0040	0.0025	
Other parameters					
β_i	0.8893*	0.9843*	0.7993*	0.8677*	0.8765*
	(0.0268)	(0.0022)	(0.0495)	(0.0581)	(0.0794)
γ_i	-0.4350*	-0.2127*	-0.0855	-0.2092	0.1749
	(0.1085)	(0.1149)	(0.0991)	(0.1669)	(0.1792)
ρ_{i2}	0.2551				
ρ_{i3}	0.3942	0.1756			
ρ_{i4}	0.3895	0.2813	0.4575		
ρ_{i5}	0.4222	0.2512	0.4671	0.5500	
ν	97.86				

Table 19 Sensitivity Test I: Stability Period I (1/1/1996 ~ 5/31/1997)

Obs. = 368	IN[1] (i = 1)	ML (i = 2)	PH (i = 3)	SG (i = 4)	TH (i = 5)
Price spillover parameters					
ϕ_{i1} (IN)	0.0690	0.0361	0.0749**	0.0299	-0.0109
	(0.0605)	(0.0372)	(0.0497)	(0.0408)	(0.0768)
ϕ_{i2} (ML)	0.0320	0.0178	0.0115	0.0004	0.0364
	(0.0534)	(0.0580)	(0.0539)	(0.0452)	(0.0803)
ϕ_{i3} (PH)	0.0252	-0.0138	0.0218	0.0114	0.0162
	(0.0456)	(0.0386)	(0.0468)	(0.0346)	(0.0660)
ϕ_{i4} (SG)	-0.0285	-0.0150	-0.0502	-0.0135	-0.0070
	(0.0685)	(0.0619)	(0.0679)	(0.0567)	(0.0960)
ϕ_{i5} (TH)	0.0202	0.0209	0.0313	0.0318**	0.0177
	(0.0252)	(0.0282)	(0.0301)	(0.0238)	(0.0521)
Volatility spillover parameters					
α_i	0.1188*	0.0576*	0.0477*	0.1078*	0.0921*
	(0.0389)	(0.0272)	(0.0211)	(0.0427)	(0.0270)
Other parameters					
β_i	0.5973*	0.8586*	0.8958*	0.6180*	0.8298*
	(0.1555)	(0.0617)	(0.0360)	(0.1630)	(0.0650)
γ_i	-0.5038*	-0.2789	-0.6314**	-0.1186	-0.1351
	(0.2414)	(0.2438)	(0.3939)	(0.1874)	(0.1532)
ρ_{i2}	0.3817				
ρ_{i3}	0.3627	0.2377			
ρ_{i4}	0.4081	0.4791	0.2879		
ρ_{i5}	0.1810	0.2244	0.1548	0.2627	
ν	35.90				

Table 20 Sensitivity Test I: Turmoil Period
(6/1/1997 ~ 3/1/1998)

Obs. = 194	IN (i = 1)	ML (i = 2)	PH (i = 3)	SG[f] (i = 4)	TH (i = 5)
Price spillover parameters					
ϕ_{i1} (IN)	0.1178**	0.1257*	0.0804*	-0.0080	0.0536
	(0.0835)	(0.0696)	(0.0439)	(0.0266)	(0.0452)
ϕ_{i2} (ML)	-0.0876	-0.1066	-0.0981**	-0.0470	-0.1111**
	(0.1037)	(0.0858)	(0.0682)	(0.0444)	(0.0825)
ϕ_{i3} (PH)	0.1750	0.1513**	0.0317	0.0360	0.0633
	(0.1564)	(0.1139)	(0.1011)	(0.0641)	(0.1035)
ϕ_{i4} (SG)	-0.2253	0.0334	0.1796	0.0821	0.0371
	(0.2441)	(0.2211)	(0.1543)	(0.0783)	(0.1328)
ϕ_{i5} (TH)	0.0377	0.0503	0.0885**	0.0476	0.1041**
	(0.1365)	(0.0895)	(0.0678)	(0.0430)	(0.0795)
Volatility spillover parameters					
α_i	0.1646*	0.0587*	0.1753*	0.0396*	0.0686*
	(0.0498)	(0.0280)	(0.0875)	(0.0211)	(0.0226)
Other parameters					
β_i	0.7340*	0.9326*	0.6215*	0.9291*	0.8854*
	(0.0885)	(0.0340)	(0.1683)	(0.0421)	(0.0604)
γ_i	-0.5098*	-0.2994	-0.0769	-0.9214	-0.0553
	(0.2164)	(0.4670)	(0.2562)	(0.7702)	(0.2845)
ρ_{i2}	0.4869				
ρ_{i3}	0.4869	0.4457			
ρ_{i4}	0.5858	0.6163	0.5790		
ρ_{i5}	0.3667	0.4678	0.4625	0.4896	
ν	21.52				

f: fail the Ljung-Box test for squared standardized residuals at the 1% level

Table 21 Sensitivity Test II: Stability Period I
(1/1/1996 ~ 8/6/1997)

Obs. = 416	IN[1] (i = 1)	ML (i = 2)	PH (i = 3)	SG (i = 4)	TH (i = 5)
Price spillover parameters					
ϕ_{i1} (IN)	0.0992*	0.0036	0.0660**	-0.0067	-0.0218
	(0.0593)	(0.0398)	(0.0507)	(0.0365)	(0.0825)
ϕ_{i2} (ML)	0.0471	0.0665	0.0354	0.0190	0.0376
	(0.0468)	(0.0578)	(0.0557)	(0.0402)	(0.0921)
ϕ_{i3} (PH)	0.0158	0.0387	0.0892*	0.0431**	0.0599
	(0.0365)	(0.0367)	(0.0446)	(0.0306)	(0.0720)
ϕ_{i4} (SG)	-0.0715	-0.0077	-0.0555	-0.0212	0.0680
	(0.0611)	(0.0647)	(0.0664)	(0.0534)	(0.1127)
ϕ_{i5} (TH)	0.0502*	0.0232	0.0233	0.0295*	0.0542
	(0.0196)	(0.0232)	(0.0244)	(0.0174)	(0.0525)
Volatility spillover parameters					
α_i	0.1739*	0.0656*	0.0322*	0.0972*	0.0647*
	(0.0411)	(0.0301)	(0.0157)	(0.0410)	(0.0202)
Other parameters					
β_i	0.5285*	0.8586*	0.9311*	0.6282*	0.9205*
	(0.1146)	(0.0595)	(0.0250)	(0.1708)	(0.0275)
γ_i	-0.8801*	-0.5754*	-0.9999**	-0.1639	-0.4684*
	(0.1833)	(0.2884)	(0.6636)	(0.2027)	(0.2134)
ρ_{i2}	0.3045				
ρ_{i3}	0.3252	0.1613			
ρ_{i4}	0.3444	0.4703	0.2479		
ρ_{i5}	0.1377	0.1211	0.0460	0.1824	
ν	45.62				

Table 22 Sensitivity Test II: Turmoil Period
(8/7/1997 ~ 3/1/1998)

Obs. = 146	IN ($i = 1$)	ML ($i = 2$)	PH ($i = 3$)	SG ($i = 4$)	TH ($i = 5$)
Price spillover parameters					
ϕ_{i1} (IN)	0.1145	0.1135	0.0779	-0.0084	0.0671
	(0.1053)	(0.1073)	(0.0608)	(0.0339)	(0.0610)
ϕ_{i2} (ML)	-0.1108	-0.1257	-0.0950	-0.0586	-0.1357
	(0.1401)	(0.1318)	(0.0921)	(0.0534)	(0.1177)
ϕ_{i3} (PH)	0.2154	0.0795	0.0356	0.0266	0.0746
	(0.2147)	(0.2064)	(0.1182)	(0.0870)	(0.1627)
ϕ_{i4} (SG)	-0.2571	0.2958	0.1411	0.1356^{**}	0.0501
	(0.2919)	(0.3648)	(0.1832)	(0.0922)	(0.1865)
ϕ_{i5} (TH)	-0.0053	0.0189	0.1020	0.0237	0.1662^{**}
	(0.1894)	(0.1633)	(0.0910)	(0.0580)	(0.1208)
Volatility spillover parameters					
α_i	0.1269^{*}	0.0236	0.0905^{**}	0.0472^{*}	0.0276
	(0.0463)	(0.0271)	(0.0647)	(0.0230)	(0.0458)
Other parameters					
β_i	0.8023^{*}	0.9723^{*}	0.8148^{*}	0.9485	0.8349
	(0.0849)	(0.0841)	(0.1241)	(0.0416)	(0.2113)
γ_i	-0.5836^{*}	-0.9762	-0.3428	-0.9969^{**}	0.7971
	(0.3184)	(1.2659)	(0.3799)	(0.7462)	(2.3777)
ρ_{i2}	0.4953				
ρ_{i3}	0.5059	0.4753			
ρ_{i4}	0.5969	0.6197	0.6081		
ρ_{i5}	0.4015	0.5242	0.5517	0.5460	
ν	24.62				

Table 23 Sensitivity Test III: Turmoil Period
(10/17/1997 ~ 6/30/1998)

Obs. = 182	IN (i = 1)	ML (i = 2)	PH (i = 3)	SG (i = 4)	TH (i = 5)
Price spillover parameters					
ϕ_{i1} (IN)	-0.0293	-0.0231	-0.0026	-0.0167	-0.0143
	(0.1094)	(0.0487)	(0.0374)	(0.0258)	(0.0356)
ϕ_{i2} (ML)	0.0314	-0.0199	0.0047	-0.0227	-0.0903
	(0.1757)	(0.0869)	(0.0723)	(0.0471)	(0.0936)
ϕ_{i3} (PH)	0.0782	0.0557	-0.0101	0.0203	-0.0162
	(0.2475)	(0.1270)	(0.1036)	(0.0809)	(0.1192)
ϕ_{i4} (SG)	-0.0563	0.1978	0.0139	0.0957	0.1594
	(0.3310)	(0.1679)	(0.1273)	(0.0935)	(0.1526)
ϕ_{i5} (TH)	0.0362	-0.0228	0.0468	0.0223	0.0832
	(0.2251)	(0.1170)	(0.0791)	(0.0552)	(0.0973)
Volatility spillover parameters					
α_i	0.0919*	0.0291**	0.0894**	0.0470*	0.0536*
	(0.0390)	(0.0200)	(0.0578)	(0.0257)	(0.0192)
Other parameters					
β_i	0.7928*	0.9542*	0.7701*	0.9340*	0.9409*
	(0.1013)	(0.0301)	(0.1597)	(0.0484)	(0.0208)
γ_i	-0.4861**	-0.0426	-0.0997	-0.7068	-0.1669
	(0.3016)	(0.4772)	(0.3052)	(0.5929)	(0.2585)
ρ_{i2}	0.4967				
ρ_{i3}	0.4961	0.4920			
ρ_{i4}	0.5570	0.6497	0.5930		
ρ_{i5}	0.4329	0.5713	0.6123	0.6003	
ν	14.16				

Table 24 Sensitivity Test III: Stability Period II
(7/1/1998 ~ 12/31/1999)

Obs. = 391	IN (i = 1)	ML (i = 2)	PH[2] (i = 3)	SG (i = 4)	TH (i = 5)
Price spillover parameters					
ϕ_{i1} (IN)	0.0315	0.0236	0.0100	0.0059	0.0038
	(0.0582)	(0.0794)	(0.0264)	(0.0199)	(0.0369)
ϕ_{i2} (ML)	-0.0593	-0.0179	0.0080	0.0171	-0.0074
	(0.0538)	(0.0604)	(0.0221)	(0.0247)	(0.0376)
ϕ_{i3} (PH)	0.0727	0.1031	0.0283	0.0005	0.0085
	(0.0910)	(0.1563)	(0.0560)	(0.0353)	(0.0653)
ϕ_{i4} (SG)	-0.0314	-0.0143	0.0761	0.0281	0.0543
	(0.0989)	(0.1677)	(0.0599)	(0.0518)	(0.0808)
ϕ_{i5} (TH)	0.0423	-0.0930	0.0094	0.0215	0.0176
	(0.0774)	(0.1269)	(0.0380)	(0.0303)	(0.0550)
Volatility spillover parameters					
α_i	0.1134*	0.0397*	0.1202*	0.0855*	0.0650*
	(0.0279)	(0.0100)	(0.0381)	(0.0334)	(0.0329)
Other parameters					
β_i	0.8062*	0.9509*	0.7734*	0.8247*	0.8284*
	(0.0470)	(0.0138)	(0.0741)	(0.0745)	(0.1151)
γ_i	0.0905	0.1944	-0.0270	-0.1463	-0.0004
	(0.1132)	(0.2809)	(0.1213)	(0.1707)	(0.1757)
ρ_{i2}	0.1779				
ρ_{i3}	0.3767	0.1126			
ρ_{i4}	0.3592	0.1726	0.4463		
ρ_{i5}	0.3802	0.1560	0.4410	0.5072	
ν	16.02				

Table 25 Sensitivity Test IV: Turmoil Period
(10/17/1997 ~ 12/31/1998)

Obs. = 314	IN (i = 1)	ML (i = 2)	PH (i = 3)	SG (i = 4)	TH (i = 5)
Price spillover parameters					
ϕ_{i1} (IN)	-0.0339	0.0318	-0.0080	-0.0133	-0.0098
	(0.0704)	(0.0622)	(0.0284)	(0.0200)	(0.0311)
ϕ_{i2} (ML)	-0.0146	-0.0487	0.0096	0.0087	-0.0009
	(0.0870)	(0.0670)	(0.0308)	(0.0261)	(0.0399)
ϕ_{i3} (PH)	0.0544	0.0130	0.0090	0.0098	0.0147
	(0.1427)	(0.1409)	(0.0668)	(0.0441)	(0.0775)
ϕ_{i4} (SG)	0.0322	0.0852	0.0340	0.0449	0.0703
	(0.1952)	(0.1822)	(0.0858)	(0.0616)	(0.0979)
ϕ_{i5} (TH)	0.0400	-0.0339	0.0181	0.0056	0.0187
	(0.1398)	(0.1435)	(0.0544)	(0.0381)	(0.0665)
Volatility spillover parameters					
α_i	0.0879*	0.0495**	0.0972*	0.0711*	0.0757*
	(0.0267)	(0.0350)	(0.0376)	(0.0233)	(0.0203)
Other parameters					
β_i	0.8062*	0.6329*	0.7658*	0.8804*	0.8885*
	(0.0661)	(0.4694)	(0.1109)	(0.0483)	(0.0332)
γ_i	-0.2015	0.5746	0.0304	-0.3163**	0.0014
	(0.1896)	(0.6503)	(0.1723)	(0.2025)	(0.1388)
ρ_{i2}	0.3984				
ρ_{i3}	0.4615	0.3116			
ρ_{i4}	0.5189	0.4347	0.5627		
ρ_{i5}	0.4468	0.3972	0.5653	0.6043	
ν	12.39				

Table 26 Sensitivity Test IV: Stability Period II
(1/1/1999 ~ 12/31/1999)

Obs. = 259	IN (i = 1)	ML (i = 2)	PH (i = 3)	SG (i = 4)	TH (i = 5)
Price spillover parameters					
ϕ_{i1} (IN)	0.0906**	0.0074	0.0188	0.0059	0.0152
	(0.0689)	(0.0517)	(0.0265)	(0.0217)	(0.0398)
ϕ_{i2} (ML)	-0.1218*	0.0923*	0.0216	-0.0047	<-0.0000
	(0.0713)	(0.0536)	(0.0400)	(0.0388)	(0.0652)
ϕ_{i3} (PH)	0.1299	0.0139	-0.0081	0.0054	-0.0090
	(0.1257)	(0.1081)	(0.0722)	(0.0589)	(0.0983)
ϕ_{i4} (SG)	-0.1675**	0.1152	0.0396	0.0152	0.0569
	(0.1183)	(0.1108)	(0.0606)	(0.0688)	(0.0942)
ϕ_{i5} (TH)	0.1330**	-0.0441	0.0277	0.0524**	-0.0155
	(0.1027)	(0.0800)	(0.0373)	(0.0400)	(0.0644)
Volatility spillover parameters					
α_i	0.1295*	-0.0042	0.1338*	0.0834*	0.0374*
	(0.0366)	(0.0219)	(0.0468)	(0.0404)	(0.0223)
Other parameters					
β_i	0.7988*	0.8456**	0.7057*	0.8424*	0.9077*
	(0.0676)	(0.5545)	(0.0935)	(0.0857)	(0.0789)
γ_i	-0.0378	-0.9523	-0.1827	-0.1771	-0.0356
	(0.1348)	(6.6677)	(0.1892)	(0.2342)	(0.2250)
ρ_{i2}	0.0550				
ρ_{i3}	0.3479	0.1705			
ρ_{i4}	0.3059	0.2429	0.3676		
ρ_{i5}	0.2894	0.1938	0.4079	0.4172	
ν	19.40				