

Dynamic Correlation Analysis of Financial Contagion: Evidence from Asian Markets

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Abstract

We apply a dynamic conditional correlation model to nine Asian daily stock-return data from 1990 to 2003. The empirical evidence confirms a contagion effect. By analyzing the correlation-coefficient series, we identify two phases of the Asian crisis. The first shows an increase in correlation (contagion); the second shows a continued high correlation (herding). Statistical analysis of the correlation coefficients also finds a shift in variance during the crisis period, casting doubt on the benefit of international portfolio diversification. Evidence shows that international sovereign credit-rating agencies play a significant role in shaping the structure of dynamic correlations in the Asian markets.

JEL Classification: F30, G15

Keywords: Financial Contagion; Asian Crises; Herding; Dynamic conditional correlation; Sovereign credit-rating

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1. Introduction

During the period from July 1997 through early 1998, Asian financial markets experienced a series of financial distresses, which spread rapidly and sequentially from one country to another in a short interval of intense crises. Later on, it spread further to Russia and Latin America. The short-term damage of the crisis not only caused asset prices to plunge across these markets but also created speculative runs and capital flight, leading to considerable financial instability for the entire region. A longer-run consequence triggered by the crisis and its spillover effect was that it brought about a dramatic loss of confidence for investors who had intended to invest in Asian markets, jeopardizing the economic growth of the region. Such a shift in the attitudes of investors may produce prolonged damage to portfolio investments because their concerns may not subside until another successful story of economic growth in the region develops, and that may take a long time. As such, academic researchers and policy makers alike have paid close attention to identifying the channels of shock transmission across countries and to measuring the damaging impact of crises on the environment for investments in Asian markets.

Since the financial shocks and the contagion process in the Asian crisis episode were attributable to a variety of factors beyond economic linkages, many researchers have focused on financial contagion by providing evidence of significant increases in cross-country correlations of stock returns and/or volatility in the region (Sachs, et al., 1996).

Yet, the existence of contagion in relation to the crisis remains a debatable issue. Some studies show a significant increase in correlation coefficients during the Asian crisis and conclude that there was a contagion effect (Baig and Goldfajn, 1999). Other researchers find that after accounting for heteroskedasticity, there is no significant increase in correlation between asset returns in pairs of crisis-hit countries, reaching the conclusion that there was “no contagion, only interdependence” (Forbes and Rigobon, 2002; Bordo and Murshid, 2001; Basu, 2002).¹ However, in their tests for financial contagion based on a single-factor model, Corsetti et al. (2005) find “some contagion, some interdependence.” Further, focusing on different transmission channels, Froot et al. (2001) and Basu (2002) confirm the existence of the contagion effect.² Thus, the evidence on the financial contagion is not conclusive.

The existing literature on the empirical research of financial contagion has several limitations and drawbacks. First, there is a heteroskedasticity problem when measuring correlations, caused by volatility increases during the crisis. Second, in addition to a lagged dependent variable, an omitted variable problem arises in the estimation of cross-country correlation coefficients due to the lack of availability of consistent and compatible financial

¹ Forbes and Rigobon (2002) define *contagion* as significant increases in cross-market co-movement. Any continued high level of market correlation suggests strong linkages between the two economies and is defined as *interdependence*. Following this line of argument, contagion must involve a dynamic increment in correlation.

² Pritsker (2001) summarizes four types of transmission channels: the correlated information channel (von Furstenberg and Jeon, 1989; King and Wadhvani, 1990) or the wake-up call hypothesis (Sachs et al., 1996), liquidity channel (Forbes, 2004; Claessens et al., 2001), the cross-market hedging channel (Kodres and Pritsker, 2002; Calvo and Mendoza, 2000), and the wealth effect channel (Kyle and Xiong, 2001). Although a direct test for identifying specific transmission channels of financial contagion may be more fruitful, it is not an easy task to implement due to the lack of microstructure data for investors or without a priori identification of the relevant fundamental variables. Thus, many of the empirical research papers on the analysis of contagion effects turn to the investigation of asset-return co-movements, applying various forms of correlation analyses. Along this line, contagion is defined as a significant increase in correlation between asset returns in different markets

data in Asian markets. Third, since *contagion* is defined as significant increases in cross-market co-movements, while any continued market correlation at high levels is considered to be *interdependence* (Forbes and Rigobon, 2002), the existence of contagion must involve evidence of a dynamic increment in correlations. Thus, the dynamic nature of the correlation needs to be sorted out. Fourth, a common problem encountered by these studies is the fact that virtually all of the tests are affected by identifying the source of crisis and the choice of window length (Billio and Pelizzon, 2003). Moreover, the choice of subsamples conditioning on high and low volatility is both arbitrary and subject to a selection bias (Boyer et al., 1999).³ Fifth, it is generally recognized that indicators of sovereign creditworthiness represented by sovereign credit ratings announced by international credit rating agencies and publications are based on economic fundamentals; the changes in ratings are perceived to reflect an external assessment of the risk associated with changes in economic fundamentals or political risk, which should have an impact on stock returns and, in turn, the correlation coefficients (Beers, et al., 2002; Kaminsky and Schmukler, 2002).⁴ Sovereign rating downgrades in one country may create an international contagion effect through the wake-up call to neighboring countries that have similar macroeconomic environments and the cross-market hedging channels. Baig and Goldfajn (1999) find an increase in the correlations in the sovereign spread during the crisis

³ Fong (2003) uses a bivariate regime-switching model by pairing the U.S. stock market with four other major stock markets and allowing for correlations to switch endogenously as a function of volatility jumps of a particular country. The extent of correlation jumps is generally small and statistically significant only for Canada. However, Fong's finding (2003) also admits that the model shares the same limitation as models in the previous literature in that it assumes one country (the United States) to be the only source of volatility shocks.

⁴ Beers, et al. (2002) note that "Standard & Poor's sovereign credit ratings are an assessment of each government's ability and willingness to service its debt in full and on time." The appraisal of each sovereign's overall creditworthiness is based on a number of measures of economic and financial performance. The information includes political risk, income and economic structure, economic growth prospects, fiscal stability, monetary stability, offshore and contingent liabilities, external liquidity, and various debt burdens.

periods as compared to tranquil periods. Their analysis, however, lacks dynamic elements and fails to provide a systematic framework to capture the invention from credit rating changes.

To overcome the limitations found in the existing literature, this paper employs a cross-country, multivariate GARCH model, which is appropriate for measuring time-varying conditional correlations. This methodology will enable us to address the heteroskedasticity problem raised by Forbes and Rigobon (2002) without arbitrarily dividing the sample into two sub-periods.⁵ In the meantime, using lagged U.S. stock returns as an exogenous factor and estimating the system simultaneously help us to resolve the omitted variable problem and, at the same time, to account for the global common factor.⁶ More important, the model provides a mechanism to trace the time-varying correlation coefficients for a group of Asian stock markets. Analyzing the derived time series of correlation coefficients allows us to detect dynamic investor behavior in response to news and innovations. Particularly, our empirical analysis provides new evidence of the significant impact of sovereign credit rating changes around the announcement dates, domestic and foreign, on cross-country correlation coefficients of stock returns in the Asian countries. This new insight will be informative for global investors, helping them to make better decisions with regard to asset and risk management, including asset allocation, portfolio diversification, and hedging strategy (Fong, 2003).

⁵ The GARCH model featuring constant conditional correlations can be found in the paper of Longin and Solnik (1995). It can also be used to identify factors that affect conditional correlation, but it can deal with only one factor at a time, creating too many parameters.

⁶ For instance, in the FR study, Hong Kong is assumed to be the source of contagion. This treatment fails to take into account the fact that during the crisis period, adverse news in each crisis country could trigger financial market turbulence in any other neighboring country. The model thus suffers from a simultaneous-equation bias.

The major findings of this paper are summarized as follows. First, this study, which uses a longer data span, finds supportive evidence of contagion during the Asian-crisis period, resolving the puzzle of “no contagion, only interdependence” reported by Forbes and Rigobon (2002). Second, two different phases of the Asian crisis are identified. The first phase, from the start of the crisis to November 17, 1997, entails a process of increasing volatility in stock returns due to contagion spreading from the earlier crisis-hit countries to other countries. In this phase, investor trading activities are governed mainly by local (country) information. However, in the second phase, from the end of 1997 through 1998, as the crisis grew in public awareness, the correlations between stock returns and their volatility are consistently higher, as evidenced by herding behavior. Statistical analysis of correlation coefficients shows shifts in the level as well as in the variance of correlations, casting some doubt on the benefit of international portfolio diversification during the crises. Third, after controlling for the variables involved in the crisis period, we find that the correlation coefficients respond sensitively to changes in sovereign credit ratings. This indicates that both market participants and financial credit-rating agents have their own dynamic roles in shaping correlation coefficients.

The remainder of the paper proceeds as follows. Section 2 describes the data and statistics of stock returns. Section 3 examines the correlation coefficients based on a simple correlation analysis by adjusting the impact of volatility during different sample periods. Section 4 presents a multivariate GARCH model and discusses its application to our context. Section 5 reports the estimation results and tests the time-varying correlation coefficients in response to different shocks. Section 6 contains conclusions.

2. Data and Descriptive Statistics

The data used in this study are daily stock-price indices from January 1, 1990, through March 21, 2003, for eight Asian countries that were seriously affected by the 1997 Asian financial crisis. The data set consists of the stock indices of Thailand (Bangkok S.E.T. Index), Malaysia (Kuala Lumpur SE Index), Indonesia (Jakarta SE Composite Index), the Philippines (Philippines SE Composite Index), South Korea (Korea SE Composite), Taiwan (Taiwan SE Weighted Index), Hong Kong (Hang Seng Index), and Singapore (Singapore Straits Times Index). In addition, two stock indices from industrial countries, Japan (Nikkei 225 Stock Average Index) and the United States (S&P 500 Composite Index), are included. All the national stock price indices are in local currency, dividend-unadjusted, and based on daily closing prices in each national market. Japan was affected by the Asian crisis, but at a much later stage and to a lesser extent. The inclusion of the United States is due mainly to the fact that the U.S. market serves as a global factor in the region. All the data were obtained from *Datastream International*.

Following the conventional approach, stock returns are calculated as the first difference of the natural log of each stock-price index, and the returns are expressed as percentages.⁷

⁷ Stock-market returns in Forbes and Rigobon (2002) are calculated as rolling-average, two-day returns on each country's stock index to control for the fact that markets in different countries are not open during the same hours. In terms of Hong Kong (HK) time, opening and closing times for each market are:

Country	HK	JP	KO	IN	PH	TH	SG	MA	TW
Open (am)	10:00	8:00	8:00	10:30	9:30	10:55	9:00	9:00	9:00
Close (pm)	16:00	14:00	14:00	17:00	12:00	18:00	17:00	17:00	13:30

Some of these markets have breaks at noon. In this paper, we do not use rolling-average, two-day returns, since no difference was found in their sensitivity tests using different ways to calculate stock returns (see Table V in FR's paper, 2002). Moreover, using two-day returns tends to generate serial correlation, and this type of measurement is not compatible for use in examining the announcement effect, which is defined as being on a daily basis. Our analysis (not reported) also finds no significant difference using daily vs. two-day returns. The results are available upon request.

When data were unavailable, because of national holidays, bank holidays, or any other reasons, stock prices were assumed to stay the same as those of the previous trading day.

The summary statistics of stock-index returns in the eight Asian countries, Japan, and the United States are presented in Table 1. As noted by various media reports, the Thai government gave up defending the value of its currency, the baht, on July 2, 1997, which triggered a significant depreciation of the currencies of Thailand and its neighboring Asian nations. Therefore, we use this date to break the entire sample into two sub-periods: pre-crisis and post-crisis. When the first two moments for the two sub-periods are compared, stock returns are generally higher during the pre-crisis period, while variances are higher during the post-crisis period. Another noteworthy statistic of the stock-return series shown in Table 1 is a high value of kurtosis. This suggests that, for these markets, big shocks of either sign are more likely to be present and that the stock-return series may not be normally distributed. Almost all of the stock-return series are found to have first-order autocorrelation for the daily data. The existence of this autocorrelation may result from nonsynchronous trading of the stocks that make up the index. It could also be due to price limitations imposed on the index or other types of market friction, producing a partial adjustment process.

[Insert Table 1 about here]

To visualize the returns for each market, we depict the series in Figure 1. With the exceptions of Taiwan and Japan, the plots show a clustering of larger return volatility around and after mid 1997. This market phenomenon has been widely recognized and successfully captured by GARCH types of models in the finance literature (Bollerslev et al., 1992).

[Insert Figure 1 about here]

3. Correlation Analyses

Since correlation analysis has been widely used to measure the degree of financial contagion, it is convenient to start our investigation by checking the simple pair-wise correlation between the stock returns for the countries under investigation. However, correlation coefficients across countries are likely to increase during a highly volatile period. That is, if a crisis hits Country A with increasing volatility in its stock market, it will be transmitted to Country B with a rise in volatility and, in turn, the correlation of stock returns in both Country A and Country B.

To address the issue of heteroskedasticity, we calculate the heteroskedasticity-adjusted correlation coefficients proposed by Forbes and Rigobon (2002; FR hereafter).⁸ We then use the standard Z -test for statistical inference.⁹ A potential problem with this analysis is that the source of contagion has to be identified beforehand. For the

⁸ FR propose an adjusted correlation coefficient, ρ^* , as: $\rho^* = \frac{\rho}{\sqrt{1 + \delta[1 - (\rho)^2]}}$ with $\delta = \frac{VAR(r_2)_h}{VAR(r_2)_l} - 1$,

where ρ is the unadjusted correlation coefficient (varying with the high- or low-volatility period),

$$\rho = Corr(r_1, r_2) = \frac{Cov(r_1, r_2)}{\sqrt{Var(r_1)Var(r_2)}} = \frac{\beta_1 Var(r_2)}{\sqrt{[\beta_1^2 Var(r_2) + Var(v_1)]Var(r_2)}} = \left[1 + \frac{Var(v_1)}{\beta_1^2 Var(r_2)} \right]^{-1/2},$$

where $r_{1,t}$ and $r_{2,t}$ are stock returns in Countries 1 and 2 at time t , respectively, in the equation $r_{1,t} = \beta_0 + \beta_1 r_{2,t} + v_{1,t}$ and $v_{1,t}$ is a stochastic noise independent of $r_{2,t}$; δ is the relative increase in the variance of r_2 ; $VAR(r_2)_h$ and $VAR(r_2)_l$ are the variance of r_2 in a high-volatility period and a low-volatility period, respectively.

⁹ Morrison (1983) suggests the test statistic for a null hypothesis of no increase in correlation: $T = \frac{Z_0 - Z_1}{\text{var}(Z_0 - Z_1)}$, where $Z_0 = \frac{1}{2} \ln\left(\frac{1 + \rho_0}{1 - \rho_0}\right)$ and $Z_1 = \frac{1}{2} \ln\left(\frac{1 + \rho_1}{1 - \rho_1}\right)$ are Fisher transformations of correlation coefficients before and after the crisis, and $\text{var}(Z_0 - Z_1) = \text{sqr}[1/(N_0 - 3) + 1/(N_1 - 3)]$ with $N_0 = 1956$ and $N_1 = 1493$ as the number of observations before and after the crisis. The test statistic is approximately normally distributed and is fairly robust to the non-normality of correlation coefficients. Basu (2002) and Corsetti et al. (2005) have employed this test.

convenience of comparison with research in the literature, both Thailand (with a breakpoint of July 2, 1997) and Hong Kong (with a breakpoint of October 17, 1997), respectively, are considered as the source of contagion in this study.¹⁰

The results are reported in Table 2A. In both cases, although the contagion effects (based on correlation coefficients having adjusted for heteroskedasticity) are not as significant as those being calculated without adjusting for heteroskedasticity, some evidence shows that correlation coefficients increase significantly after the crisis occurs, producing somehow different results from those reported in FR's study. As will be shown at a later point, the main difference is due to the different data length used in estimating the turmoil period.¹¹

[Insert Table 2A about here]

This new evidence also raises a question about whether the source country of contagion matters. To address this question, we recalculated the adjusted correlation coefficients based on the order in which infected countries were impacted during the crisis.¹² It follows that 31 pair-wise correlation coefficients are calculated and tested.¹³ The results show that, before correction, the null hypothesis of no correlation increase is rejected by 29 out of 31 coefficients, which is consistent with FR's finding. As shown in Table 2B, after the

¹⁰ FR argue that during the Asian crisis, the events in Asia became headline news in the world only after the Hong Kong market declined sharply in October 1997. Therefore, they use Hong Kong as the only source of contagion and October 17, 1997, as the breakpoint of the whole sample period.

¹¹ A comparison with FR's result will be given in the discussion of Figure 3 and footnote 28.

¹² The order of these countries is Thailand (managed float of the baht on July 2, 1997), the Philippines (wider float of the peso on July 11, 1997), Malaysia (float of the ringit on July 14, 1997), Indonesia (float of the rupiah on August 14, 1997), Singapore (large decline in stock and currency markets on August 28, 1997), Taiwan (large decline in stock and currency markets on October 17, 1997), Hong Kong (large decline in stock market on October 17, 1997), Korea (float of won on November 17, 1997), and Japan (stock-market crash on December 19, 1997). Their respective breakpoints are also used, with similar results.

¹³ There are $(1+8)*8/2=36$ pair-wise correlations with five correlation decreases in the case of Malaysia.

relative volatility is corrected, though, the contagion effect is moderate; yet we still find that the null hypothesis is rejected at the 10 percent level in 16 out of 31 cases.

[Insert Table 2B about here]

The simple-correlation analysis with correction for heteroskedasticity highlights the significance of market volatility in a given window. However, market behavior is expected to change continuously in response to ongoing shocks. In the next section, we discuss this issue further by employing a multivariate GARCH model to capture the information of the time-varying characteristics of the correlation matrix.

4. The Dynamic Correlation Coefficient Model

The multivariate GARCH model proposed by Engle (2002), which is used to estimate dynamic conditional correlations (DCC) in this paper, has three advantages over other estimation methods.¹⁴ First, the DCC-GARCH model estimates correlation coefficients of the standardized residuals and thus accounts for heteroskedasticity directly. Second, the model allows us to include additional explanatory variables in the mean equation to ensure that the model is well specified. In this connection, we include U.S. stock returns as an exogenous global factor, rather than using the source of contagion (e.g., stock returns in Thailand) as an independent variable. Third, the multivariate GARCH model can be used to examine multiple asset returns without adding too many parameters.¹⁵ The parsimonious parameter setting permits us to deal with up to 45 pair-wise correlation coefficient series in

¹⁴ Another type of multivariate GARCH model with constant conditional correlation (CCC) is also used to estimate the correlation coefficients by splitting the sample period into two, using July 2, 1997, as the breakpoint. The results are very similar to those in unconditional correlation analysis. In 34 pair-wise correlation increases, 30 are significant before correction for heteroskedasticity and 20 are still significant after the correction.

¹⁵ Other types of multivariate GARCH models, such as the full vec model and the BEKK model (Engle and Kroner, 1995) would become costly in estimation time if expanded to three asset returns.

a single representation. The resulting estimates of time-varying correlation coefficients provide us with dynamic trajectories of correlation behavior for national stock-index returns in a multivariate setting. This information enables us to analyze the correlation behavior when there are multiple regime shifts in response to shocks, crises, and credit-rating changes.

To start with, we specify the return equation as:

$$r_t = \gamma_0 + \gamma_1 r_{t-1} + \gamma_2 r_{t-1}^{US} + \varepsilon_t, \quad (1)$$

where $r_t = (r_{1,t}, r_{2,t}, \dots, r_{n,t})'$, $n=10$; $\varepsilon_t = (\varepsilon_{1,t}, \varepsilon_{2,t}, \dots, \varepsilon_{n,t})'$; and $\varepsilon_t | \mathfrak{F}_{t-1} \sim N(0, H_t)$.

Following the conventional approach, an AR(1) term and the one-day lagged U.S. stock return are included in the mean equation. The AR(1) is used to account for the autocorrelation of stock returns, which was found in almost all the countries under investigation, as reported in Table 1. The lagged U.S. stock returns have often been used to account for a global factor (Dungey, et al., 2003).¹⁶ The inclusion of the lagged U.S. stock returns is also based on the empirical finding that U.S. stock returns play an important role in determining stock returns in Asian countries and that Asian stock returns have no significant dynamic effect on U.S. stock returns. Next, we specify a multivariate conditional variance as:

$$H_t = D_t R_t D_t, \quad (2)$$

¹⁶ At this stage, we include neither exchange-rate changes nor interest-rate changes in the mean equations. During the crisis, exchange rates change discretely. Our study (not reported), which is consistent with the finding reported by Kallberg et al. (2005), indicates that exchange-rate changes can explain only a very small portion of stock-market changes during the crisis. In addition, the interest-rate data for these Asian countries do not have a consistent measurement and fail to reflect free market operation due to government intervention, which makes it inappropriate to include interest-rate changes in this study, which uses daily data. As Baig and Goldfajn (1999) argue, overnight call rates were widely used as tools of monetary policy so that they reflect more about the policy stance than about the market-determined levels.

where D_t is the $(n \times n)$ diagonal matrix of time-varying standard deviations from univariate GARCH models with $\sqrt{h_{ii,t}}$ on the i^{th} diagonal, $i = 1, 2, \dots, n$; R_t is the $(n \times n)$ time-varying correlation matrix. The DCC model proposed by Engle (2002) involves two-stage estimation of the conditional covariance matrix H_t . In the first stage, univariate volatility models are fitted for each of the stock returns and estimates of $\sqrt{h_{ii,t}}$ are obtained. In the second stage, stock return residuals are transformed by their estimated standard deviations from the first stage. That is, $u_{i,t} = \varepsilon_{i,t} / \sqrt{h_{ii,t}}$, where $u_{i,t}$ is then used to estimate the parameters of the conditional correlation. The evolution of the correlation in the DCC model is given by:

$$Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha u_{t-1}u_{t-1}' + \beta Q_{t-1}, \quad (3)$$

where $Q_t = (q_{ij,t})$ is the $n \times n$ time-varying covariance matrix of u_t , $\bar{Q} = E[u_t u_t']$ is the $n \times n$ unconditional variance matrix of u_t , and α and β are nonnegative scalar parameters satisfying $(\alpha + \beta) < 1$.¹⁷ Since Q_t does not generally have ones on the diagonal, we scale it to obtain a proper correlation matrix R_t . Thus,

$$R_t = (\text{diag}(Q_t))^{-1/2} Q_t (\text{diag}(Q_t))^{-1/2}, \quad (4)$$

where $(\text{diag}(Q_t))^{-1/2} = \text{diag}(1/\sqrt{q_{11,t}} \cdots 1/\sqrt{q_{nn,t}})$.

¹⁷ A typical element of Q_t is given by: $q_{ij,t} = (1 - \alpha - \beta)\bar{\rho}_{ij} + \alpha u_{i,t-1}u_{j,t-1} + \beta q_{ij,t-1}$, where $\bar{\rho}_{ij}$ is the unconditional correlations of $u_{i,t}u_{j,t}$.

Now R_t in equation (4) is a correlation matrix with ones on the diagonal and off-diagonal elements less than one in absolute value, as long as Q_t is positive definite.¹⁸ A typical element of R_t is of the form:

$$\rho_{ij,t} = q_{ij,t} / \sqrt{q_{ii,t}q_{jj,t}}, \quad i, j = 1, 2, \dots, n, \text{ and } i \neq j. \quad (5)$$

Expressing the correlation coefficient in a bivariate case, we have:

$$\rho_{12,t} = \frac{(1 - \alpha - \beta)\bar{q}_{12} + \alpha u_{1,t-1}u_{2,t-1} + \beta q_{12,t-1}}{\sqrt{[(1 - \alpha - \beta)\bar{q}_{11} + \alpha u_{1,t-1}^2 + \beta q_{11,t-1}][(1 - \alpha - \beta)\bar{q}_{22} + \alpha u_{2,t-1}^2 + \beta q_{22,t-1}]}}. \quad (6)$$

As proposed by Engle (2002), the DCC model can be estimated by using a two-stage approach to maximizing the log-likelihood function. Let θ denote the parameters in D_t , and ϕ the parameters in R_t , then the log likelihood fund is:

$$l_t(\theta, \phi) = \left[-\frac{1}{2} \sum_{t=1}^T (n \log(2\pi) + \log |D_t|^2 + \varepsilon_t' D_t^{-2} \varepsilon_t) \right] + \left[-\frac{1}{2} \sum_{t=1}^T (\log |R_t| + u_t' R_t^{-1} u_t - u_t' u_t) \right]. \quad (7)$$

The first part of the likelihood function in Equation (7) is volatility, which is the sum of individual GARCH likelihoods. The log-likelihood function can be maximized in the first stage over the parameters in D_t . Given the estimated parameters in the first stage,

¹⁸ Tse and Tsui (2002) present a different form of DCC model by using $R_t = (1 - \alpha - \beta)R + \alpha\Psi_{t-1} + \beta R_{t-1}$, where R is symmetric $n \times n$ positive definite parameter matrix with $\rho_{ii}=1$, Ψ_{t-1} is the $n \times n$ correlation

matrix of error term. Its i,j -th element is given by: $\psi_{ij,t-1} = \frac{\sum_{m=1}^M u_{i,t-m} u_{j,t-m}}{\sqrt{(\sum_{m=1}^M u_{i,t-m}^2)(\sum_{h=1}^M u_{j,t-m}^2)}}$.

the correlation component of the likelihood function in the second stage (the second part of Equation (7)) can be maximized to estimate correlation coefficients.

5. Evidence from Dynamic Correlations for the Hardest-Hit Country Group

5.1 Estimates of the Model

Table 3 reports the estimates of the return and conditional variance equations. The AR(1) term in the mean equation is significantly positive for Thailand, Indonesia, Malaysia, Philippines, and Singapore, while it is significantly negative for Hong Kong and Japan. This finding is in agreement with the evidence in the literature in that the AR(1) is positive in emerging markets due to price friction or partial adjustment and that AR(1) is negative as the presence of positive feedback trading in advanced markets (Antoniou et al., 2005). However, AR(1) is not significant for Korea, Taiwan, and the United States. Consistent with most studies on Asian markets (Dungey et al., 2003), the effect of U.S. stock returns on Asian stock returns is, on average, highly significant and consistently large in magnitude, ranging from 0.155 (Indonesia) to 0.474 (Hong Kong). The coefficients for the lagged variance and shock-squared terms in the variance equation are highly significant, which is consistent with time-varying volatility and justifies the appropriateness of the GARCH (1,1) specification. Note that the sum of the estimated coefficients (see last column) in the variance equation, $(a + b)$, is close to unity for all of the cases, implying that the volatility displays a highly persistent fashion.

[Insert Table 3 about here]

An advantage of using this model, as it stands, is the fact that all possible pair-wise correlation coefficients (45) for the 10 countries in the sample can be estimated in a

single-system equation.¹⁹ To simplify the presentation and reduce unnecessary parameterizations in calculation, we examine the dynamic patterns of correlation changes by focusing on the hardest-hit countries, including Thailand, Indonesia, Malaysia, the Philippines, Korea, and Hong Kong.²⁰

5.2 Two Phases of the Crisis

Figure 2 shows pair-wise conditional correlation coefficients between the stock returns of Thailand and those of Indonesia, Malaysia, the Philippines, Korea, and Hong Kong during the period 1996-2003.²¹ These time-series patterns show that the pair-wise conditional correlations increased during the second half of 1997 and reached their highest level in 1998. Although all six countries were hit hard, the stock returns of Thailand during the early stages of the crisis showed very low correlations (as low as -0.055) with the stock returns of the other five countries.²² However, throughout 1998, the correlations became significantly higher and persisted at the higher levels, ranging from 0.3 to 0.47, before declining at the end of 1998.²³

¹⁹ The contemporary correlation coefficients between U.S. stock returns and Asian stock returns may have less practical meaning due to time zone differences. The Asian stock returns in day t are expected to be the most affected by U.S. stock returns in day $t-1$.

²⁰ Hong Kong is added to the analysis because of its significance in relation to Asian markets and it is convenient for comparing our result with the literature in a similar setting (Forbes and Rigobon, 2002).

²¹ We also produce a figure for the time-varying correlation coefficients, starting from 1990, to capture some events associated with the shocks during the early 1990s (not shown). The information shows that during the Gulf War in 1990 and 1991, the correlations increased almost 200 percent. During 1994 and 1995, the correlation coefficients also increased substantially, which might be due to the crisis in Mexico. However, none of these events were shown to be as significant as the Asian crisis.

²² It should be noted that the low correlation in mid 1997 is not evidence against the contagion effect. Our explanation will be provided at a later point.

²³ Most of the correlation coefficients started to decline around October 20, 1998. A similar model is run for the exchange-rate changes in these countries. However, relative to the stock markets, the currency markets had less activity and the estimated pair-wise correlation coefficients could not explain all of the correlation changes in the stock markets. The evidence is consistent with results reported by Kallberg et al. (2005). One possible explanation is that the currency markets received more government intervention, setting a fixed parity relation with the U.S. dollar.

[Insert Figure 2 about here]

Consistent with the observations made by Bae et al. (2003) and Kallberg et al. (2005), our study provides evidence of contagion effects in these Asian stock markets in the early phases of the crisis and then a transition to herding behavior in the latter phases. Here contagion and herding behavior are distinguished in the sense that contagion describes the spread of shocks from one market to another with a significant increase in correlation between markets, while herding describes the simultaneous behavior of investors across different markets with high correlation coefficients in all markets.²⁴ Our interpretation is that in the early phases of the crisis, investors focus mainly on local country information, so that contagion takes place. As the crisis becomes public news, investor decisions tend to converge due to herding behavior, creating higher correlations. Specifically, when Thailand depreciated its currency, investors were focusing on asset management in Thailand's market, paying very little attention to other countries' markets. As investors began to withdraw their funds from Thailand and reinvest in other countries in the region, this action resulted in decreased correlations at the beginning of the crisis. As more and more asset prices declined in neighboring countries due to the contagion effect spreading through various channels, investors began to panic and withdraw funds from all of the Asian economies.²⁵ During this process, the convergence of market consensus and the

²⁴ As noted by Hirshleifer and Teoh (2003), herding/dispersing is defined to include any behavioral similarity/dissimilarity brought about by actual interactions of individuals. Herding is a phenomenon of convergence in response to sudden shifts of investor sentiment or due to cross-market hedging. It should be mentioned that observation of others can lead to dispersing instead of herding if preferences are opposing.

²⁵ Kaminsky et al. (2000) indicate that bond and equity flows to Asia collapsed from their peak of US\$38 billion in 1996 to US\$9 billion in 1998. In particular Taiwan, Singapore, Hong Kong, and Korea experienced, respectively, 12.91 percent, 11.75 percent, 6.91 percent, and 6.49 percent average net selling (as a percentage of the holdings at the end of the preceding quarter) in the first two quarters following the outbreak of the crisis.

stock returns in these economies showed a gradual increase in correlation. This phenomenon is identified as the first phase of the crisis.

Given the increasing uncertainty in the markets, the cost of collecting credible information is relatively high during such a period, and investors are likely to follow major investors in making their own investing decisions. Any public news about one country may be interpreted as information regarding the entire region. That is why we see consistently high correlations in 1998; this phenomenon is a result of herding behavior and identified as the second phase. As observed, the second phase started when South Korea was impacted and floated its currency, the won, on November 17, 1997. Thereafter, news in any country would affect other countries, representing the period of the most widespread panic.²⁶

5.3 Statistical Analysis of Correlation Coefficients in Different Phases of the Crisis

As shown in Figure 2, the pair-wise conditional-correlation coefficients between stock returns of these Asian countries were seen to be persistently higher and more volatile in the second phase of the crisis. This leads to two important implications from the investor's perspective. First, a higher level of correlation implies that the benefit from market-portfolio diversification diminishes, since holding a portfolio with diverse country stocks is subject to systematic risk. Second, a higher volatility of the correlation coefficients suggests that the stability of the correlation is less reliable, casting some doubts on using the estimated correlation coefficient in guiding portfolio decisions. For these reasons, we need to look into the time-series behavior of correlation coefficients and sort out the impacts of external shocks on their movements and variability.

²⁶ Applying the threshold-cointegration model to daily exchange rates, both spot and forward, Jeon and Seo (2003) identify the exact breakpoint as November 18, 1997, for the Korean won, and August 15, 1997, for the Thai baht.

Using three dummy variables for different sub-samples allows us to investigate the dynamic feature of the correlation changes associated with different phases of crises. The regression model is given by:

$$\rho_{ij,t} = \sum_{p=1}^P \phi_p \rho_{ij,t-p} + \sum_{k=1}^3 \alpha_k DM_{k,t} + e_{ij,t} \quad (8)$$

where $\rho_{ij,t}$ is the pair-wise correlation coefficient between the stock returns of Thailand and the other crisis countries of Indonesia, Malaysia, Hong Kong, Korea, and the Philippines, such that $i = \text{Thailand}$; $j = \text{Indonesia, Malaysia, Hong Kong, Korea, and the Philippines}$. The lag length in equation (8) is determined by the AIC criterion. $DM_{1,t}$ is a dummy variable for the first phase of the crisis period (7/2/1997-11/17/1997); $DM_{2,t}$ is a dummy variable for the second phase of the Asian crisis (11/18/1997-12/31/1998); $DM_{3,t}$ is the dummy variable for the post-crisis period (1/1/1999-3/21/2003). Since our pre-tests using ARCH-LM statistics find significant heteroskedasticity in all cases,²⁷ three dummy variables, $DM_{k,t}$ ($k = 1, 2, 3$), are added to a GARCH(1,1) specification. The conditional variance equation is given by

$$h_{ij,t} = A_0 + A_1 h_{ij,t-1} + B_1 \varepsilon_{ij,t-1}^2 + \sum_{k=1}^3 d_k DM_{k,t} \quad (9)$$

As the model implies, the significance of the estimated coefficients on the dummy variables indicates structural changes in mean or/and variance shifts of the correlation coefficients due to external shocks during the different phases of the crisis.

²⁷ LM tests for Indonesia, Malaysia, Philippines, and Korea using ARCH(4) are 34.26, 421.51, 181.27, and 127.06, respectively. The absence of an ARCH effect is rejected uniformly.

The estimates using the maximum-likelihood method for the GARCH (1,1) model are reported in Table 4. The evidence shows that none of the $DM_{1,t}$ in the mean equation is statistically significant, indicating that the correlation during the early phase of the crisis is not significantly different from that of the pre-crisis period. This may reveal the fact that there was a drop in the correlation coefficients at the beginning of the crisis because the news may be considered as a single-country case and the crisis signal has not been fully recognized.

[Insert Table 4 about here]

However, as time passes and investors gradually learn the negative news affecting market development, they start to follow the crowds, i.e, they begin to imitate more reputable and sophisticated investors. As the threat of investment losses becomes more widespread, the dispersed market behavior gradually converges as information accumulates, leading to more uniform behavior and producing a higher correlation. At the moment when any public news about one country is interpreted as information for the entire region, the correlation becomes more significant. This is seen in the second phase of the crisis, as reflected by a significant rise in all the coefficients on $DM_{2,t}$ in the mean equation. This finding is consistent with the co-movement paths shown in Figure 2 and supports the herding behavior hypothesis in the second phase of the crisis. Obviously, the herding phenomenon will negate the benefit of holding a diversified international portfolio in the region.

In the post-crisis period, the correlation coefficients, as shown in the estimates of $DM_{3,t}$, decreased significantly in all cases except Korea and Hong Kong, where the stock markets might still have been experiencing some hangover effect. For the rest of the

markets, as expected, investors became more rational in analyzing the fundamentals of the individual markets rather than herding after others. Thus, the correlations between market returns declined. The high correlation between the stock returns of Thailand and Korea as well as between Thailand and Hong Kong after the crisis is consistent with the wake-up call hypothesis, where investors realized that there was some similarity between the two markets' fundamentals after the crisis. Therefore, their trading strategy was based on related information from both markets.²⁸

As most asset-return models reported, all of the estimates of the lagged variance and shock-squared terms are highly significant, displaying a clustering phenomenon. Moreover, the evidence shows that the correlation coefficients between two markets profoundly changed after the occurrence of the Asian crisis. As shown in the lower part of Table 4, the coefficients on $DM_{1,t}$ and $DM_{2,t}$ are positive and highly significant, indicating more volatile changes in the correlation coefficients in the first and second phases of the crisis; the explosive changes in volatility even extended into the post-crisis period as indicated by the significance of the coefficients on $DM_{3,t}$. The evidence thus suggests that when the crisis hits the market, the correlation coefficients could vary greatly, and this variability could be prolonged for a significant period of time. As a result, the estimates and statistical inference of risk from risk models based on constant correlation coefficients can be very misleading.

²⁸ Estimations are also conducted to investigate the possible existence of a contagion effect between Japan and the crisis countries. Our results (not reported) show that the impact of the Asian crisis on Japan is not as dramatic as events such as the 1990 Gulf War or the September 11, 2001 attacks. Starting from early 1998, the correlation coefficients rise gradually and reach a high value of around 0.25 during the Russia crisis and the near-default of the U.S. hedge fund Long-Term Capital Management (LTCM) in the global stock markets. Our evidence is consistent with the findings of Arestis et al. (2003) that contagion from the Asian crisis countries to Japan took place in early 1998. The contagion from the Asian-crisis countries to Japan was relatively slow and moderate as compared with other events or factors.

It is of interest to compare this model with the model presented by Forbes and Rigobon (2002). To elucidate, we depict both the dynamic Thailand-HK correlation coefficient series (reproduced from Figure 2) and the constant correlation coefficient series in Figure 3. The solid line shows the time-varying correlation derived from the DCC-GARCH model for the period from January 1, 1996, to December 31, 1998. The broken lines show FR's heteroskedasticity-adjusted correlation (AB and CD) for the Thailand-HK pair from January 1, 1996, to November 16, 1997, using October 17, 1997 as a breakpoint for defining stable and turmoil periods.²⁹ Two observations are immediately apparent by comparing two estimates. First, the constant correlation model fails to reveal the time-varying feature and, hence, is unable to reflect the dynamic market conditions. Second, the estimated coefficient for the constant correlation model, even with an adjustment for heteroskedasticity, is conditional on the sample size of the regime or the length of the window for calculating. For instance, by estimating the correlation coefficients based on FR's sample periods, we obtain the estimated values of 0.098 and 0.042 for the stable period (line AB) and the turmoil period (line CD), respectively. By extending the turmoil period to a longer sample period, as we have done in this paper, the correlation coefficient jumps up to 0.244, as shown in a broken line EF in Figure 3.

²⁹ Constant correlation coefficients are estimated using the following basic VAR model in FR (2002):

$$X_t = \phi(L)X_t + \eta_t$$

$$X_t = \{x_t^c, x_t^j\}'$$

where x_t^c is the two-day average stock market return in Hong Kong (crisis country), x_t^j is the two-day average stock return in another country, $\phi(L)$ is a 2x2 matrix of lag L , and η_t is a vector of disturbance terms. As in FR's paper, $L = 5$. This is the same specification as the fifth to last row in Table V in FR's paper (2002). We also estimate and compare our model with that of FR by varying lags and return definition; no significant difference is found. Our paper differs from FR's in two aspects. First, a longer sample is used to satisfy large sample properties. Second, time-varying coefficients are derived based on the DCC-GARCH(1,1) model. A detailed report of the estimated results is available from the authors upon request.

Thus, our finding is consistent with FR's analysis if a longer sample period is included. However, the dynamic correlation coefficient is able to capture the dynamic elements continually emerging from the market.

[Insert Figure 3 about here]

5.4 The Effect of Sovereign Credit-Rating Changes on Correlation Coefficients

It should be noted that the noise of the correlation coefficients in equation (8) might be sensitive to news, local or global. The news that received substantial attention from policy makers and investors during the 1997 Asian financial crisis included the announcements of changes in foreign-currency sovereign credit ratings for a particular country in the region. To incorporate this information into the model, equation (8) is rewritten as:

$$\rho_{ij,t} = \phi_0 + \phi_1 \rho_{ij,t-1} + \sum_{k=1}^3 \alpha_k DM_{k,t} + \sum_{s=-1}^1 \omega_{1s} I_{i,t-s}^{(T_s)} + \sum_{s=-1}^1 \omega_{2s} I_{j,t-s}^{(T_s)} + v_{ij,t}, \quad (10)$$

where $I_t^{(T_s)}$ is an indicator (intervention) variable for measuring the impulse effect of news that reaches the market at time $t = T$. In this context, $I_{i,t}^{(T_s)}$ and $I_{j,t}^{(T_s)}$ are used to capture the effect of sovereign credit-rating changes in its own country i and a foreign country j with a window length of s , spanning from $(T-1)$ to $(T+1)$; ω_{1s} and ω_{2s} are constant coefficients. The sovereign credit-rating changes can take place in market i , Thailand, and/or in market j , comprised of Indonesia, Malaysia, the Philippines, Korea, and Hong Kong.

The indicator variable for $s = -1, 0,$ and 1 takes the form of:

$$I_{i(j),t}^{(T_s)} = \begin{cases} \Delta v, & (t = T_s) \\ 0, & (t \neq T_s) \end{cases} \quad (11)$$

where Δv denotes changes in the sovereign credit ratings and outlooks reported by Standard and Poor's. For instance, for an upgrade of one notch, we set $I_{i,t}^{(T_s)} = 1$; for a downgrade of 2, we set $I_{i,t}^{(T_s)} = -2$. If there is an outlook change from positive to stable or from stable to negative, the rating is changed by $-1/3$. If an outlook changes from positive to negative, then the rating is changed by $-2/3$. The binary settings for $I_{i,t}^{(T_s)}$, which reflect rating changes and/or "outlook changes" and the on-watch or off-watch list of markets under investigation, are summarized in the Appendix.³⁰

To provide an illustration of the influence of news about sovereign credit-rating changes in its own and foreign countries on cross-country correlation coefficients, we estimate equation (10) for Thailand as country i and Indonesia, Malaysia, the Philippines, Korea, or Hong Kong as country j . The estimation results of equation (10) and equation (9) are reported in Table 5. The evidence shows that all of the markets are negatively influenced by the sovereign credit-rating changes in Thailand; the coefficients for Indonesia, Malaysia, the Philippines, and Korea as a foreign country are all statistically significant with a one-day lag. However, a positive significant effect is found in Indonesia and Hong Kong markets in the contemporaneous term.³¹ With respect to the impact of

³⁰ We construct a similar indicator variable for measuring exchange-rate intervention. There is no significant effect on the indicator. For this reason, we do not report the results.

³¹ It is a rather complex job to determine the sign of sovereign credit ratings on the correlation coefficient. One possible reason is the different speeds in reacting to announcements. For instance, if stock returns in both Thailand and Hong Kong react instantaneously to rating changes, but with different speeds, the pair-wise correlation coefficient is likely to decline. Thus, a negative news announcement is seen to be positively related to the correlation coefficient. On the other hand, if stock returns in the Philippines covary with those of Thailand with the same speed, the correlation coefficient will be positive; an announcement of bad news on the rating change will have a negative effect on the correlation coefficient. The sign will be more uncertain if information lags received by respective agents occur. This can be more difficult if agents have a limited ability to corroborate government data to form investment or sovereign credit-rating decisions. Moreover, the rating reflects mainly political risk and economic fundamentals, while the correlation coefficient variations can also be affected by market momentum.

foreign rating changes on correlations, the statistics indicate that the coefficients on both Indonesia and Hong Kong are significant. Putting the information together suggests that investors in Indonesia and Hong Kong markets have more significant and sensitive responses to the announcements of rating changes, domestic and foreign. The joint tests based on the F-statistics (F_R) also find strong supporting evidence of the significant effect of sovereign credit-rating changes, domestic and foreign, on cross-country correlation coefficients of stock returns. Further checking the Lung-Box Q statistic and the ARCH test finds that, with some minor exceptions, the serial correlations in both the error and error-squared series are considered “adequate.”

[Insert Table 5 about here]

In conclusion, empirical analysis of the correlation coefficients suggests that in addition to structural changes appearing at different phases of the crisis, news about sovereign credit-rating changes in its own and foreign countries has a significant impact on pair-wise cross-country stock return correlations between the Asian markets around announcement dates. The evidence is in line with the intervention analysis in time series of stock-return correlations, while market participants and credit-rating agents both play dynamic roles in shaping the cross-country correlation coefficients of stock returns in the Asian countries.

6. Conclusions

This paper investigates the relationship between the stock returns of various crisis-hit countries during the 1997-98 Asian financial crises. Heteroskedasticity-adjusted simple correlation analysis with an extended length of window as well as dynamic correlation analysis concludes that there is evidence of contagion effects during the Asian financial

crisis, a finding that does not agree with the “no contagion” conclusion reached by Forbes and Rigobon (2002).

While examining stock-market contagion and herding behavior, we apply a dynamic multivariate GARCH model to analyze daily stock-return data in the Asian market during the 1996 to 2003 period. This study identifies two phases of the Asian crisis. In the first phase, the crisis displays a process of increasing correlations, while in the second phase, investor behavior converges and correlations are significantly higher across the Asian countries in the sample. One possible explanation is that the contagion effect takes place early in the crisis and that herding behavior dominates the latter stages of the crisis.

The apparent high correlation coefficients during crisis periods implies that the gain from international diversification by holding a portfolio consisting of diverse stocks from these contagion countries declines, since these stock markets are commonly exposed to systematic risk. Moreover, the high volatility of correlation coefficients implies the presence of either an unstable covariance or an erratic variance, or both. The uncertainty of the estimated coefficients thus provides less reliable statistical inferences, which may misguide portfolio decisions.

An important finding emerging from our investigation of the dynamic behavior of stock-return correlations is that the cross-country correlation structure of stock returns is subject to structural changes, both in level and in variability. The correlation coefficients are found to be significantly influenced by news about changes in foreign-currency sovereign credit ratings in its own and foreign countries. This study suggests that both investors and international rating agents play significant roles in shaping the structure of dynamic correlations in the Asian markets.

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Appendix

The information about changes in foreign-currency sovereign credit ratings for five Asian crisis countries during the period from July 1, 1997, to December 31, 1998, is obtained from Standard and Poor's *CreditWeek*. Long-term foreign-currency sovereign credit ratings represent a country's likelihood of defaulting on foreign-currency-denominated sovereign bonds. The rating scales of the Standard and Poor's ratings are as follows. The highest band is "A," which has seven notches: AAA, AA+, AA, AA-, A+, A, A-. The next band is the "B" level rating, which has nine notches: BBB+, BBB, BBB-, BB+, BB, BB-, B+, B, B-. The lowest band has six notches: CCC+, CCC, CCC-, CC, SD (selective default) and D. Outlook changes and the on-watch or off-watch list are also included in our study, since they may have the same information content as rating changes. There are three outlook scales: positive, stable, and negative. The on-watch or off-watch list is treated the same as outlook changes. In order to use these ratings, numerical values are attached. Since there are a total of 22 notches, where the lowest rating never shows up in the sample, the highest rating AAA is assigned 20 and the SD is assigned 0. A negative outlook will add nothing to the value, while stable and positive outlooks add 1/3 and 2/3 to the rating values, respectively. The rating changes are summarized in the following table.

[Insert Table A1 about here]

Table A1. The Intervention Variable for Rating Changes (07/01/1997 - 12/31/1998)

Thailand	$I_i^{(T_s)} = -1/3$ (T_s : August 1, 1997), $= -1$ (T_s : September 3, 1997; January 8, 1998), $= -2$ (T_s : October 24, 1997), otherwise $=0$.
Indonesia	$I_j^{(T_s)} = -1$ (T_s : October 10, 1997; January 9, 1998; January 27; March 11, 1998; May 15, 1998), $= -4/3$ (T_s : December 31, 1997), $= -3$ (T_s : January 27, 1998), otherwise $=0$;
Malaysia	$I_j^{(T_s)} = -1/3$ (T_s : August 18, 1997; September 25, 1997), $= -1$ (T_s : December 23, 1997), $= -4/3$ (T_s : April 17, 1998; July 24, 1998), $= -2$ (T_s : September 15, 1998), otherwise $=0$;
Philippines	$I_j^{(T_s)} = -1/3$ (T_s : September 25, 1997; February 23, 1998), otherwise $=0$;
Korea	$I_j^{(T_s)} = -1/3$ (T_s : August 6, 1997), $= -1$ (T_s : October 24, 1997), $= -2$ (T_s : November 25, 1997), $= -3$ (T_s : December 11, 1997), $= -4$ (T_s : December 22, 1997), $= 1/3$ (T_s : January 16, 1998), $= 3$ (T_s : February 17, 1998), otherwise $=0$.
Hong Kong	$I_j^{(T_s)} = -1/3$ (T_s : December 4, 1992; June 12, 1998), $= -2/3$ (T_s : February 12, 1990), $= -1$ (T_s : August 31, 1998), $= 1/3$ (T_s : December 7, 1999), $= 2/3$ (T_s : February 13, 1995; May 14, 1997), $= 1$ (T_s : February 8, 2001), otherwise $=0$.

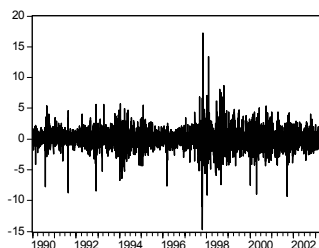
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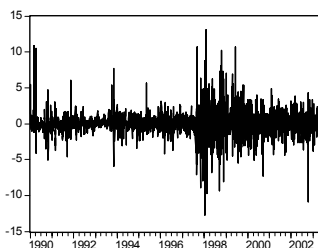
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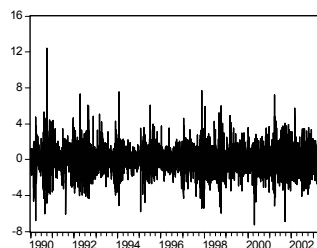
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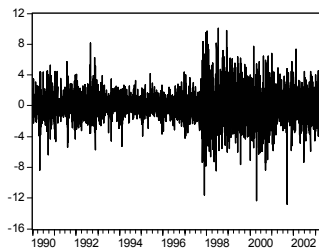
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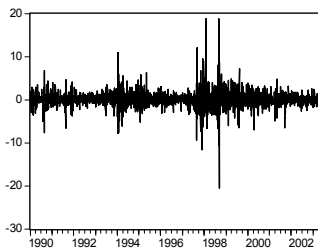
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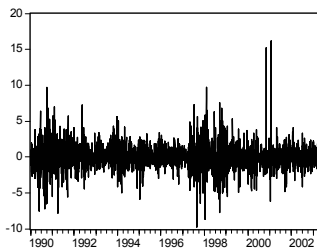
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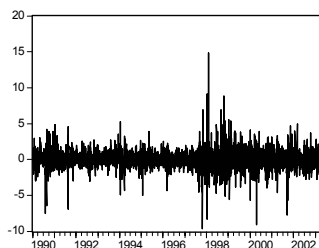
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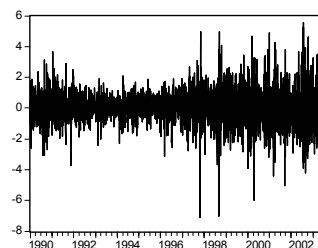
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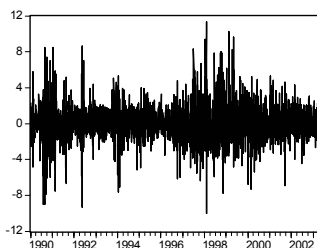
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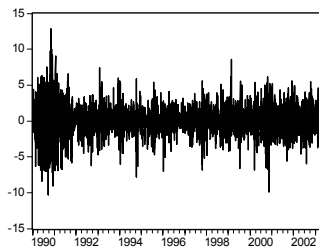
SG



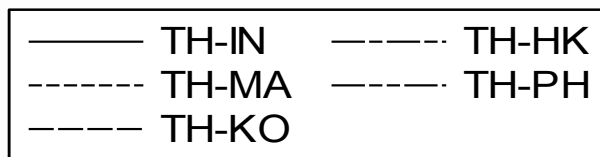
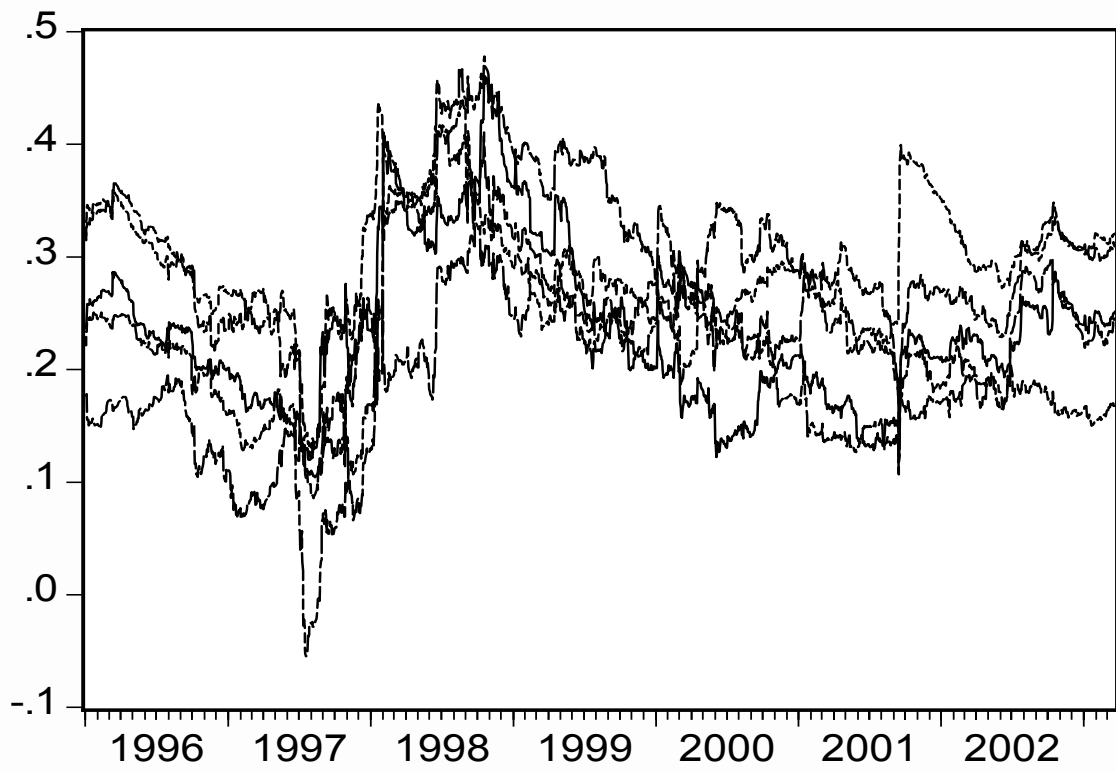
US



TH



TW



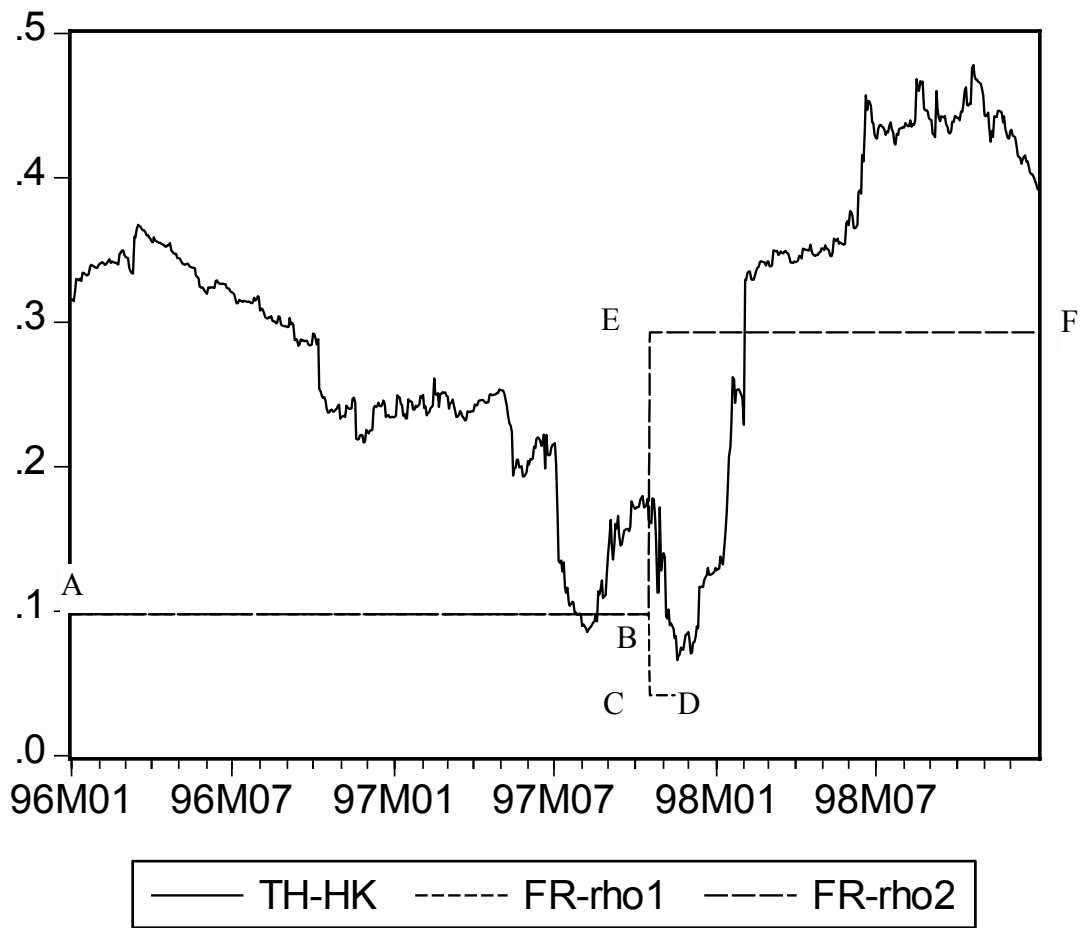


Figure 1. Daily Stock Returns (1/1/1990-3/21/2003)

HK, IN, JP, KO, MA, PH, SG, US, TH, and TW, respectively, represent the stock returns of Hong Kong, Indonesia, Japan, Korea, Malaysia, the Philippines, Singapore, the U.S., Thailand, and Taiwan. All stock returns are 100 times first differences of natural logarithms of the stock indices.

Figure 2. GARCH-corrected correlations between the stock returns of Thailand and those of the other five crisis countries (1996-2003)

Figure 3. Dynamic and constant correlation coefficients of the stock returns between Thailand and Hong Kong (1996-2003)

Table 1
Descriptive Statistics on Stock Returns (1/1/1990-3/21/2003)

	Mean	Variance	Skewness	Kurtosis	LB(16)
<i>Panel A: Before the crisis</i>					
HK	0.086	1.765	-0.512***	5.017***	25.856*
Indonesia	0.031	0.984	1.500***	19.141***	285.714***
Japan	-0.034	2.093	0.423***	5.098***	31.772**
Korea	-0.009	1.965	0.255***	2.799***	15.695
Malaysia	0.037	1.517	-0.045	8.906***	91.287***
Philippines	0.048	2.273	0.052	4.001***	134.326***
Singapore	0.026	1.009	-0.396***	6.308***	102.874***
Taiwan	-0.003	4.592	-0.076	3.493***	39.952***
Thailand	-0.026	2.741	-0.247***	5.294***	54.835***
US	0.047	0.535	-0.165***	2.249***	28.813**
<i>Panel B: After the crisis</i>					
HK	-0.034	4.112	0.219***	8.524***	37.392***
Indonesia	-0.041	4.182	0.169***	5.973***	81.438***
Japan	-0.060	2.474	0.099	1.864***	15.741
Korea	-0.018	6.611	-0.050	1.949***	24.175*
Malaysia	-0.045	4.030	0.696***	22.882***	61.591***
Philippines	-0.067	3.020	1.009***	12.308***	76.848***
Singapore	-0.025	2.818	0.419***	8.241***	50.762***
Taiwan	-0.045	3.329	0.054	1.755***	32.718***
Thailand	-0.025	4.153	0.622***	3.751***	64.678***
US	0.0004	1.808	-0.025	2.148***	15.801

Notes: Observations for all series in the whole sample period are 3449. The observations for the pre-crisis and post-crisis sub-periods are 1956 and 1493, respectively. ***, **, and * denote statistical significance at the 1%, 5% and 10% levels, respectively. All variables are first differences of the natural log of stock indices times 100.^b LB(16) refers to Ljung Box statistics with a 16-day lag.

Table 2A

Test of significant increases in correlation coefficients (Thailand and Hong Kong as the source of contagion, respectively)

	Correlation before crisis	Correlation after crisis	Adj. Correlation after crisis	Z-Stat (Unadjusted)	Z-stat (Adjusted)
<i>Thailand as the source:</i>					
TH-HK	0.310	0.372	0.310	-2.041**	0.012
TH-IN	0.158	0.341	0.283	-5.695***	-3.817***
TH-JP	0.148	0.229	0.188	-2.443***	-1.189
TH-KO	0.141	0.311	0.257	-5.224***	-3.515***
TH-PH	0.211	0.314	0.260	-3.220***	-1.494*
TH-SG	0.391	0.454	0.383	-2.231**	0.290
TH-TW	0.141	0.206	0.169	-1.949**	-0.822
<i>Hong Kong as the source:</i>					
HK-TH	0.286	0.398	0.278	-3.702***	0.245
HK-PH	0.211	0.354	0.245	-4.524***	-1.035
HK-IN	0.203	0.334	0.230	-4.094***	-0.813
HK-SG	0.512	0.650	0.496	-6.114***	0.629
HK-TW	0.139	0.272	0.185	-4.032***	-1.371*
HK-JP	0.254	0.437	0.308	-6.069***	-1.719**
HK-KO	0.084	0.361	0.250	-8.553***	-4.990***

Notes: HK, IN, JP, KO, PH, SG, TH, and TW represent the stock returns of Hong Kong, Indonesia, Japan, Korea, the Philippines, Singapore, Thailand, and Taiwan, respectively.

Adjustment of the correlation is given in Footnote (8). Z-tests are given in Footnote (9). The null hypothesis is no increase in correlation. The 1%, 5%, and 10% critical values for a one-sided test of the null are -2.32, -1.64, and -1.28, respectively. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Malaysia is not included due to a decrease in correlation after the crisis.

Table 2B

Test of significant increases in simple correlation coefficients

	Correlation before crisis	Correlation after crisis	Adj. Correlation after crisis	Z-Stat (Unadjusted)	Z-stat (Adjusted)
TH-HK	0.310	0.372	0.310	-2.041**	0.012
TH-IN	0.158	0.341	0.283	-5.695***	-3.817***
TH-JP	0.148	0.229	0.188	-2.443***	-1.189
TH-KO	0.141	0.311	0.257	-5.224***	-3.515***
TH-PH	0.211	0.314	0.260	-3.220***	-1.494*
TH-SG	0.391	0.454	0.383	-2.231**	0.290
TH-TW	0.141	0.206	0.169	-1.949**	-0.822
PH-HK	0.200	0.351	0.309	-4.763***	-3.402***
PH-IN	0.188	0.312	0.274	-3.852***	-2.644***
PH-JP	0.082	0.183	0.159	-2.992***	-2.286**
PH-KO	0.053	0.215	0.188	-4.807***	-3.977***
PH-SG	0.266	0.407	0.361	-4.636***	-3.053***
PH-TW	0.139	0.146	0.127	-0.208	0.355
MA-IN	0.208	0.262	0.164	-1.662***	1.316
MA-KO	0.108	0.215	0.134	-3.197***	-0.763
MA-TW	0.142	0.171	0.106	-0.864	1.066
IN-HK	0.172	0.339	0.172	-5.211***	-0.007
IN-JP	0.060	0.198	0.098	-4.087***	-1.098
IN-KO	0.015	0.184	0.090	-4.975***	-2.201**
IN-SG	0.222	0.404	0.210	-5.892***	0.380
IN-TW	0.043	0.155	0.076	-3.292***	-0.960
SG-HK	0.504	0.649	0.455	-6.364***	1.861
SG-JP	0.319	0.375	0.235	-1.852**	2.638
SG-KO	0.133	0.356	0.222	-6.934***	-2.683***
SG-TW	0.174	0.284	0.175	-3.379***	-0.017
TW-HK	0.141	0.267	0.309	-3.828***	-5.174***
TW-JP	0.143	0.218	0.254	-2.255**	-3.357***
TW-KO	0.094	0.260	0.302	-4.995***	-6.307***
HK-JP	0.251	0.433	0.300	-6.021***	-1.550*
HK-KO	0.077	0.355	0.241	-8.547***	-4.918***
KO-JP	0.047	0.317	0.092	-8.177***	-1.326*

Notes: See notes in Table 2A. For the cases displaying a decrease in correlation, pair-wise correlations between the stock returns in Malaysia and those in Thailand, the Philippines, Hong Kong, Japan, and Singapore will not be reported.

Table 3
 Estimation results from the GARCH-DCC model

	Return Equations				Variance Equations		
	γ_0	γ_1	γ_2	c	a	b	Persistence
TH	0.0448*	0.057***	0.228***	0.0615***	0.878***	0.109***	0.987
	(1.756)	(4.173)	(8.733)	(4.979)	(88.771)	(12.057)	
IN	0.0162	0.218***	0.155***	0.0137***	0.894***	0.117***	1.011
	(0.972)	(15.163)	(8.778)	(4.333)	(131.86)	(13.279)	
MA	0.0551***	0.129***	0.218***	0.0256***	0.892***	0.099***	0.991
	(3.224)	(9.856)	(14.090)	(5.817)	(117.59)	(13.084)	
KO	0.0145	0.001	0.324***	0.0454***	0.908***	0.082***	0.990
	(0.498)	(0.036)	(12.374)	(4.165)	(79.678)	(8.038)	
HK	0.0885***	-0.030***	0.474***	0.0363***	0.926***	0.058***	0.984
	(4.532)	(-2.568)	(23.344)	(6.018)	(160.23)	(13.712)	
JP	-0.0005	-0.046***	0.360***	0.0488***	0.899***	0.0798***	0.978
	(-0.023)	(-3.294)	(18.270)	(7.457)	(123.41)	(13.332)	
PH	0.0289	0.157***	0.282***	0.0582***	0.889***	0.0948***	0.983
	(1.165)	(10.703)	(11.773)	(5.359)	(97.069)	(11.975)	
SG	0.0457***	0.049***	0.330***	0.0316***	0.910***	0.071***	0.981
	(3.301)	(4.073)	(18.451)	(5.219)	(85.734)	(8.789)	
TW	0.0337	0.015	0.264***	0.0607***	0.917***	0.066***	0.983
	(1.124)	(1.183)	(9.090)	(5.601)	(105.89)	(9.545)	
US	0.0559***	0.015		0.0047***	0.943***	0.055***	0.998
	(3.568)	(0.979)		(3.434)	(151.25)	(8.624)	

Notes: See Notes in Table 2A. U.S. represents U.S. stock returns. The estimates of the mean-reverting process are $\alpha = 0.006$ (7.278) and $\beta = 0.989$ (480.292). The persistence level of the variance is calculated as the summation of the coefficients in the variance equations ($a+b$). The t-statistics are in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels with critical values of 2.58, 1.96, and 1.65, respectively.

Return equations: $r_t = \gamma_0 + \gamma_1 r_{t-1} + \gamma_2 r_{t-1}^{US} + \varepsilon_t$,

where $r_t = (r_{1,t}, r_{2,t}, \dots, r_{10,t})'$, $\varepsilon_t = (\varepsilon_{1,t}, \varepsilon_{2,t}, \dots, \varepsilon_{10,t})'$, $\varepsilon_t | I_{t-1} \sim N(0, H_t)$.

Variance equations: $h_{ii,t} = c_i + a_i h_{ii,t-1} + b_i \varepsilon_{i,t-1}^2$ $i = 1, 2, \dots, 10$

Table 4

Tests of changes in dynamic correlations between national stock returns during different phases of the Asian crisis (1/1/1990-3/21/2003)

	Indonesia	Malaysia	Philippines	Korea	Hong Kong
<i>Mean Equation</i>					
Constant	0.0012*** (3.563)	0.0006*** (3.376)	0.0007*** (3.506)	0.0015*** (5.789)	0.0011*** (3.866)
ρ_{t-1}	0.9947*** (617.596)	0.9965*** (1644.042)	0.9958*** (987.179)	0.9906*** (629.207)	0.9951*** (969.677)
$DM_{1,t}$	0.0011 (0.988)	-6.39E-06 (-0.006)	0.0009 (1.382)	-5.31E-05 (-0.094)	-0.0004 (-0.380)
$DM_{2,t}$	0.0007* (1.650)	0.0007*** (2.750)	0.0007* (1.801)	0.0011*** (2.794)	0.0014*** (4.506)
$DM_{3,t}$	-0.0002 (-0.998)	0.0002 (1.531)	1.61E-05 (0.151)	0.0005*** (2.742)	0.0003** (2.021)
<i>Variance Equation</i>					
Constant	8.98E-06*** (38.033)	4.77E-06*** (28.293)	2.29E-06*** (38.054)	1.14E-06*** (26.551)	1.18E-05*** (62.028)
ε_{t-1}^2	0.3637*** (22.312)	0.5425*** (25.467)	0.3176*** (36.454)	0.1440*** (34.172)	0.7059*** (41.709)
h_{t-1}	0.3347*** (21.654)	0.3816*** (25.760)	0.7103*** (144.773)	0.8274*** (256.083)	0.0825*** (7.093)
$DM_{1,t}$	2.77E-05*** (6.773)	2.96E-05*** (7.825)	3.48E-06** (2.270)	9.04E-07* (1.699)	5.74E-05*** (7.985)
$DM_{2,t}$	1.87E-05*** (12.632)	4.18E-06*** (8.092)	1.21E-06*** (2.827)	3.11E-06*** (8.489)	1.68E-05*** (10.699)
$DM_{3,t}$	2.00E-06*** (12.032)	2.88E-06** (25.663)	-8.18E-07*** (-12.967)	6.89E-07*** (10.321)	1.45E-06*** (5.457)
Q (5)	2.709	14.895*	8.201	1.311	8.296
ARCH(5)	0.074	0.709	4.986	6.215	0.366

Notes: Estimates are based on equation (8) and equation (9) in the text. $\rho_{ij,t}$ is the correlation coefficient between the stock returns of Thailand and the other five crisis countries of Indonesia, Malaysia, the Philippines, Korea, and Hong Kong. $DM_{1,t}$ is the dummy variable for the first phase of the crisis period (7/2/1997-11/17/1997); $DM_{2,t}$ is the dummy variable for the second phase of the Asian crisis (11/18/1997-12/31/1998); and $DM_{3,t}$ is the dummy variable for the post-crisis period (1/1/1999-3/21/2003). The lag length k is determined by the AIC criterion. Q(5) is the Ljung-Box Q-statistics up to 5 days, testing the serial correlation of the residuals. ARCH(5) is the ARCH LM test up to 5 days, testing the heteroskedasticity of the residuals. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively. Numbers in parentheses are Z-statistics.

Table 5. Tests of the influence of news about sovereign credit-rating changes on across-country correlation coefficients between national stock returns (1/1/1990-3/21/2003)

	Indonesia	Malaysia	Philippines	Korea	Hong Kong
<i>Mean Equation</i>					
Constant	0.0012*** (2.722)	0.0006*** (3.299)	0.0014*** (5.213)	0.0015*** (5.792)	0.0011*** (3.840)
ρ_{t-1}	0.9944*** (542.270)	0.9966*** (1658.339)	0.9932*** (757.926)	0.9906*** (628.626)	0.9950*** (964.470)
$DM_{1,t}$	0.0006 (0.793)	-0.0003 (-0.307)	-0.0002 (-0.257)	-0.0002 (-0.362)	-0.0009 (-0.890)
$DM_{2,t}$	0.0008* (1.612)	0.0007*** (2.575)	0.0009** (2.246)	0.0011*** (2.742)	0.0014*** (4.651)
$DM_{3,t}$	-0.0002 (-0.643)	0.0002 (1.567)	-0.0002 (-1.635)	0.0005*** (2.742)	0.0003* (1.891)
$I_{i,T+1}$	-0.0007 (-0.348)	0.0030** (2.461)	-0.0003 (-0.290)	-0.0031*** (-2.971)	0.0061*** (3.653)
$I_{i,T}$	0.0056*** (3.733)	-0.0031 (-1.553)	-0.0024 (-1.009)	-0.0005 (-0.136)	0.0096*** (6.156)
$I_{i,T-1}$	-0.0064*** (-3.524)	-0.0045** (-2.462)	-0.0049*** (-3.551)	-0.0026** (-2.020)	-0.0038 (-1.357)
$I_{j,T+1}$	-0.0008*** (-3.547)	-0.0027 (-1.321)	0.0006 (0.221)	0.0003 (0.219)	-0.0029 (-0.919)
$I_{j,T}$	0.0003 (0.430)	-0.0002 (-0.074)	-0.0012 (-0.109)	-0.0013 (-0.938)	0.0037*** (3.048)
$I_{j,T-1}$	-9.14E-05 (-0.082)	-1.38E-05 (-0.006)	-0.0002 (-0.021)	0.0008 (0.373)	-0.0015 (-0.550)
<i>Variance Equation</i>					
Constant	1.42E-05*** (29.796)	4.73E-06*** (27.938)	2.41E-06*** (34.234)	1.14E-06*** (26.357)	1.24E-05*** (71.745)
ε_{t-1}^2	0.3339*** (19.299)	0.5553*** (24.640)	0.2662*** (27.553)	0.1452*** (34.098)	0.7212*** (40.529)
h_{t-1}	0.1824*** (7.422)	0.3820*** (25.253)	0.7099*** (119.470)	0.8267*** (254.793)	0.0497*** (5.177)
$DM_{1,t}$	2.01E-05*** (5.259)	1.91E-05*** (5.417)	3.62E-06** (2.373)	6.77E-07 (1.161)	4.73E-05*** (9.129)
$DM_{2,t}$	2.29E-05*** (11.913)	4.22E-06*** (8.093)	1.90E-06*** (3.682)	3.12E-06*** (8.411)	1.75E-05*** (10.520)
$DM_{3,t}$	2.68E-07 (1.349)	2.96E-06*** (25.670)	-7.28E-07*** (-10.443)	6.89E-07*** (10.276)	1.47E-06*** (5.391)
F_R	18.095***	6.352***	3.139***	2.134**	14.926***
Q(5)	1.313	14.739**	8.204	1.299	10.231*
ARCH(5)	0.043	0.707	0.800	6.444	0.452

Notes: See notes in Table 4. Estimates are based on (9) and (10) in the text.