Spillover Effects of the US Financial Crisis on Financial Markets in Emerging Asian Countries

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Abstract

We estimate dynamic conditional correlations of financial asset returns across countries by an array of multivariate GARCH models and analyze spillover effects of the recent US financial crisis on 5 emerging Asian countries. We find a symptom of financial contagion around the collapse of Lehman Brothers in September 2008. There appears to be a regime shift to substantially higher conditional correlations that persisted for a fairly short-period of time. We also propose a novel approach that allows simultaneous estimations of the conditional correlation coefficient and the effects of its determining factors over time, which can be used to identify channels of spillovers. We find the dominant role of foreign investment for the conditional correlations in international equity markets. The dollar Libor-OIS spread, the sovereign CDS premium, and foreign investment are found to play significant roles in foreign exchange markets.

Keywords: Financial Crisis, Spillover Effects, Contagion, Emerging Asian Countries, Dynamic Conditional Correlation, DCCX-MGARCH

JEL Classification: C32, F31, G15

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1 Introduction

The collapse of the US housing market and the ensuing sub-prime mortgage market crash in the Summer of 2007 triggered a global financial crisis, which is considered the first global crisis since the Great Depression (Claessens *et al.* 2010). As Dooley and Hutchison (2009) point out, financial reforms in emerging economies made it possible to temporarily insulate themselves from adverse shocks originating from the US until the Summer of 2008. This relatively tranquil period of time, however, was ended by a direct shock in the form of the Lehman failure in September 2008. The equity price in Taiwan, for instance, dropped by 38.5% in 3 months following September 15, 2008. During the same period, the Korean Won depreciated against the US dollar by 19.2% as global risk aversion spurred demand for a safe asset (ironically, US dollars), which led to strong deteriorating spillover effects on real sectors.

Even though understanding the nature of contagion in financial markets is of fundamental importance, the economic profession has failed to reach a consensus even on the existence of contagion during earlier financial crises. Forbes and Rigobon (2002), for example, argue that virtually all previous evidence of contagion (see, among others, King and Wadhwani, 1990, Lee and Kim, 1993, Calvo and Reinhart, 1996) disappears when *unconditional* cross-market correlation coefficients are corrected for bias. Corsetti *et al.* (2005), however, point out Forbes and Rigobon's test is biased towards the null hypothesis of no contagion, and report stronger evidence of contagion with an alternative test.

In this paper, we investigate the transmission of the recent US crisis to financial markets in five emerging Asian economies: Indonesia, Korea, the Philippines, Thailand, and Taiwan. We are particularly interested in the following questions. Is there empirical evidence of contagion from the US to emerging Asian financial markets? If so, when did it occur and for how long did it last? More importantly, through what channels did the contagion spread to those markets? We employ an array of multivariate generalized autoregressive conditional heteroskedasticity (MGARCH) models to seek answers to these questions.

To answer the first two questions, we employ Engle's (2002) dynamic conditional correlation

(DCC) model and a nonlinear conditional correlation MGARCH (NLCC-MGARCH) models, the exponential smooth transition (EST) model. Throughout the paper, we focus on time-varying dynamic conditional correlations during the recent crisis instead of unconditional correlation coefficients as in our view the latter lacks practical usefulness from a policy perspective. Our NLCC-MGARCH model estimations for the equity and foreign exchange markets in the US and 5 emerging Asian economies identified two substantially different conditional correlations around the Lehman episode. Overall, transitions from the tranquil period to the contagion period occurred very quickly and lasted for fairly short period of time. This implies that these countries can experience a sudden acceleration of systemic risk when exogenous shocks occur. We do not claim, however, that the conditional correlation was the highest during the crisis in the entire sample period. Instead, we demonstrate that the correlation of asset returns of the source and the victim countries tends to increase rapidly during the crisis.

To answer the third question, we propose a novel DCC-MGARCH-type model with exogenous variables (DCCX-MGARCH). To the best of our knowledge, this method is the first that estimates both the dynamic conditional correlation and the effects of explanatory variables simultaneously in a unified framework. The DCCX-MGARCH method can be quite useful to see what economic fundamental variables affect the cross-country correlations in order to identify the channels of contagion.

A number of variables can be considered for the factors that determine time-varying conditional correlations. We consider the following three channels of contagion. The first one is the factors that proxy the vulnerability of the US financial markets. We consider the VIX index for this purpose. The TED spread and the daily 3-month US dollar Libor-overnight index swap (OIS) spread are also considered as liquidity availability measures. Secondly, we use the sovereign credit default swap (CDS) premium as a proxy for weakness of emerging Asian markets. The last factor is the amount of foreign order flow (foreign investment) to quantitatively measure the role of foreign capital.

Our estimation reveals a dominant role of foreign capital for the conditional correlations in international equity markets. In foreign exchange markets, the Libor-OIS spread, the sovereign

CDS premium, and the market share of foreign investors are found to play important roles. These findings provide valuable policy implications. The importance of foreign capital, for instance, calls for institutional arrangements such as currency swap agreements.

The remainder of the present paper is organized as follows. Section 2 provides a brief literature review. In Section 3, we present our empirical models and discuss estimation techniques employed. Section 4 describes the data and presents the empirical results. Some concluding remarks and policy implications are reported in the last section.

2 Literature review

The empirical literature on spillover/contagion is extensive. There are at least two important but unsettled issues: 1) whether contagion actually occurred between countries/markets during financial crises in the past; 2) if contagion occurred, through what channels adverse shocks propagated to other countries/markets from the source.

To deal with the first issue, researchers typically employ a sub-sample analysis for a structural break (with a *known* structural break date) in unconditional cross-market correlation coefficients in the pre- and post-crisis period. If the correlation coefficient increases significantly during the crisis, this may imply statistically higher degree cross-market linkages, in other words, contagion. Examples of studies that employ such methods include: King and Wadhwani (1990), Lee and Kim (1993), Calvo and Reinhart (1996), and Baig and Goldfajn (1999), among others. Many of these papers find sizable differences in correlation coefficients and conclude contagion occurred during the crises they investigated.[1]

Forbes and Rigobon (2002) point out, however, that these tests based on sub-sample comparisons of correlation coefficients may suffer from severe bias due to heteroskedasticity.[2] Correcting

[1] King and Wadhwani (1990) investigate stock return correlations between the US, the UK, and Japan and report a significant increase in the cross-country correlation coefficients of stock returns after the 1987 US stock market crash. Lee and Kim (1993) find similar evidence from an extended data set with 12 major markets. Calvo and Reinhart (1996) find contagion between stock prices and bond prices after the 1994 Mexican crisis. Baig and Goldfajn (1999) also report evidence of cross-country contagion in the currency and equity markets during the East Asian crisis.

[2] Boyer *et al.* (1999) and Loretan and English (2000) made the same point and derive similar bias correction methods independently.

for the bias, Forbes and Rigobon report virtually no evidence of contagion during crises in the past, including the 1997 East Asian crisis, the 1994 Mexican Peso (devaluation) crisis, and the 1987 US market crash. Instead, they find a high level of correlation in all periods, which they call interdependence. Corsetti *et al.* (2005), however, point out that the tests by Boyer et al. (1999) and Forbes and Rigobon (2002) are biased towards the null hypothesis of no contagion.[3] Using a standard factor model, they report strong evidence of contagion during the 1997 Hong Kong stock market crisis.

An array of research uses GARCH-type models focusing on price-volatility spillover effects. For instance, Hamao et al. (1990) use a GARCH-M (GARCH in mean) model and report some spillover effects on the conditional mean and variance in stock markets after the 1987 US stock market crash. Edwards (1998) find similar evidence in international bonds markets after the 1994 Mexican Peso crisis. Bekaert *et al.* (2005) find no evidence of increases in "excess" stock market correlations (above the expected correlations based on economic fundamentals), contagion, after the 1994 Peso crisis, while finding some evidence of contagion after the 1997 Asian crisis. It should be noted, however, that these analysis do not provide direct evidence against those of Forbes and Rigobon (2002), because Forbes and Rigobon focus on permanent changes in unconditional moments rather than conditional ones.

Another group of researchers, including the present one, employ the dynamic conditional correlation (DCC) MGARCH model by Engle (2002) to estimate time-varying conditional correlations. This approach does not require knowledge of the exact date when the contagion occurs. Put differently, we do not make an arbitrary assumption on the timing of turmoil periods, since it does not rely on sub-sample analyses. See, among others, Chiang *et al.* (2007), Frank and Hesse (2009), and Hwang *et al.* (2010).

The second issue, though we view more important than the first one from policy perspectives, has drawn relatively less attention. Rose and Spiegel (2009), in their recent study for a cross-section of 85 countries, consider a real linkage (trade channel) and a financial linkage (foreign asset

[3] Bekaert *et al.* (2005) also point out that Forbes and Rigobon's method is not valid in the presence of common shocks.

exposure) that may have allowed the recent US crisis to spread to other countries. They find little evidence that these channels are closely related with the incidence of the crisis.[4] Contagion due to financial channels seem highly plausible, though, because a high exposure to foreign assets can lead to a rapid deterioration in a country's balance sheet when exogenous foreign adverse shocks occur (see Davis, 2008).

One way to investigate the role of financial linkages for exacerbating contagious effects is to compare dynamic conditional correlations across countries and across markets (see Frank and Hesse, 2009, for example). Our DCCX-MGARCH model is different from such models in that ours *directly* estimates the effects of exogenous variables on the time-varying conditional correlations in a unified MGARCH framework. To the best of our knowledge, this is a novel aspect of our model. Since it provides information on what variables play dominant roles for channelling adverse shocks from the source country to the recipient countries, it is possible to make more suitable policy suggestions.

3 The Econometric Model

3.1 The Dynamic Conditional Correlation Model

We first employ the dynamic conditional correlation (DCC) estimator (Engle, 2002) for multivariate generalized autoregressive conditional heteroskedasticity (MGARCH) models to estimate time-varying conditional correlations of international asset returns. DCC-MGARCH can be viewed as a generalization of the constant conditional correlation (CCC) estimator (Bollerslev, 1990).

Let $\mathbf{y}_t = [y_{1,t} \;\; y_{2,t} \;\; \cdots \;\; y_{k,t}]'$ be a $k \times 1$ vector of asset returns that obeys the following stochastic process.

$$\mathbf{y}_t = \mathbf{\Gamma}(L)\mathbf{y}_{t-1} + \mathbf{e}_t, \tag{1}$$

where $\mathbf{\Gamma}(L)$ is the lag polynomial matrix. The conditional distribution of asset returns is assumed

[4] For articles that investigate trade linkages, see Eichengreen *et al.* (1996), Glick and Rose (1999), Eichengreen and Rose (1998), and Forbes and Chinn (2004), among others.

to be joint normal,

$$\mathbf{e}_t|\Omega_{t-1} \sim \mathcal{N}(\mathbf{0}, \mathbf{H}_t), \tag{2}$$

where Ω_{t-1} is the adaptive information set at time $t-1$. The conditional covariance matrix $\mathbf{H}_t$ is defined as,

$$\mathbf{H}_t = \mathbf{D}_t \mathbf{R}_t \mathbf{D}_t, \tag{3}$$

where $\mathbf{D}_t$ is the diagonal matrix with the conditional variances along the diagonal, $\mathbf{D}_t = diag\left(h_{i,i,t}^{1/2}\right)$ and $\mathbf{R}_t$ is the time-varying correlation matrix.[5]

The equation (3) can be re-parameterized as follows with standardized returns, $\varepsilon_t = \mathbf{D}_t^{-1}\mathbf{e}_t$,

$$\mathbb{E}_{t-1}\varepsilon_t\varepsilon_t^{'} = \mathbf{D}_t^{-1}\mathbf{H}_t\mathbf{D}_t^{-1} = \mathbf{R}_t = [\rho_{i,j,t}] \tag{4}$$

Engle proposes the following mean-reverting conditional correlations with the GARCH$(1,1)$ specification.

$$\rho_{i,j,t} = \frac{q_{i,j,t}}{\sqrt{q_{i,i,t}q_{j,j,t}}}, \tag{5}$$

where

$$q_{i,j,t} = \bar{\rho}_{i,j}(1-\alpha-\beta) + \alpha\varepsilon_{i,t-1}\varepsilon_{j,t-1} + \beta q_{i,j,t-1}, \tag{6}$$

and $\bar{\rho}_{i,j}$ is the unconditional correlation between $\varepsilon_{i,t}$ and $\varepsilon_{j,t}$. α and β are non-negative scalars that satisfy $\alpha+\beta<1$.[6] In matrix form,

$$\mathbf{Q}_t = \bar{\mathbf{Q}}\,(1-\alpha-\beta) + \alpha\varepsilon_{t-1}\varepsilon_{t-1}^{'} + \beta\mathbf{Q}_{t-1}, \tag{7}$$

where $\bar{\mathbf{Q}}$ is the unconditional correlation matrix of ε_t. $\mathbf{R}_t$ is obtained by

$$\mathbf{R}_t = (\mathbf{Q}_t^*)^{-1/2}\,\mathbf{Q}_t\,(\mathbf{Q}_t^*)^{-1/2}, \tag{8}$$

[5] Bollerslev's CCC model assumes $\mathbf{H}_t = \mathbf{D}_t\mathbf{R}\mathbf{D}_t$, where $\mathbf{R}$ is a $k \times k$ time-invariant (symmetric) correlation matrix.

[6] When $\alpha+\beta=1$, $q_{i,j,t}$ is nonstationary and the exponential smoothing estimator can apply.

where $\mathbf{Q}_t^* = diag\left\{\mathbf{Q}_t\right\}$.

Engle proposes a two-step approach for estimating the DCC model. The log-likelihood function for our bivariate model is,

$$\begin{aligned}
\mathcal{L} &= -\frac{1}{2}\sum_{t=1}^{T}\left(2\log(2\pi)+\log|\mathbf{H}_t|+\mathbf{e}_t'\mathbf{H}_t^{-1}\mathbf{e}_t\right) \\
&= -\frac{1}{2}\sum_{t=1}^{T}\left(2\log(2\pi)+\log|\mathbf{D}_t\mathbf{R}_t\mathbf{D}_t|+\mathbf{e}_t'\mathbf{D}_t^{-1}\mathbf{R}_t^{-1}\mathbf{D}_t^{-1}\mathbf{e}_t\right) \\
&= -\frac{1}{2}\sum_{t=1}^{T}\left(2\log(2\pi)+2\log|\mathbf{D}_t|+\log|\mathbf{R}_t|+\varepsilon_t'\mathbf{R}_t^{-1}\varepsilon_t\right)
\end{aligned} \tag{9}$$

Adding and subtracting $\mathbf{e}_t'\mathbf{D}_t^{-1}\mathbf{D}_t^{-1}\mathbf{e}_t = \varepsilon_t'\varepsilon_t$ to (9) and rearranging, we obtain the log-likelihood as the sum of the volatility component ($\mathcal{L}_V$) and correlation component ($\mathcal{L}_C$). Let θ denote a vector of parameters in $\mathbf{D}_t$ and ϕ be other parameters in $\mathbf{R}_t$.

$$\mathcal{L}(\theta,\phi) = \mathcal{L}_V(\theta) + \mathcal{L}_C(\theta,\phi), \tag{10}$$

where

$$\begin{aligned}
\mathcal{L}_V(\theta) &= -\frac{1}{2}\sum_{t=1}^{T}\left(2\log(2\pi)+\log|\mathbf{D}_t|^2+\mathbf{e}_t'\mathbf{D}_t^{-2}\mathbf{e}_t\right) \\
&= -\frac{1}{2}\sum_{t=1}^{T}\sum_{i=1}^{2}\left(\log(2\pi)+\log\left(h_{i,i,t}\right)+\frac{e_{i,t}^2}{h_{i,i,t}}\right) \\
\mathcal{L}_C(\theta,\phi) &= -\frac{1}{2}\sum_{t=1}^{T}\left(\varepsilon_t'\mathbf{R}_t^{-1}\varepsilon_t-\varepsilon_t'\varepsilon_t+\log|\mathbf{R}_t|\right)
\end{aligned}$$

One may obtain the parameter estimates $\hat{\theta}$ by maximizing $\mathcal{L}_V(\theta)$. Given $\hat{\theta}$, maximization of $\mathcal{L}_C\left(\hat{\theta},\phi\right)$ yields the estimates for ϕ.

3.2 The Nonlinear Conditional Correlation Model

Notwithstanding its usefulness in investigating the time-varying nature of conditional correlations, the DCC-MGARCH model is not suitable to detect a regime shift in conditional correlations between international asset returns, since it estimates continuously time-varying correlation coefficients. For this purpose, we employ a nonlinear conditional correlation MGARCH (NLCC-MGARCH) model similar to the one proposed by Berben and Jansen (2005). We assume that the conditional covariance matrix $\mathbf{H}_t$ in (2) obeys the following stochastic process.

$$\begin{aligned} h_{1,1,t} &= \omega_1 + \alpha_1 e_{1,t-1}^2 + \beta_1 h_{1,1,t-1} \\ h_{2,2,t} &= \omega_2 + \alpha_2 e_{2,t-1}^2 + \beta_2 h_{2,2,t-1} \\ h_{1,2,t} &= \rho(s_t)\left(h_{1,1,t} h_{2,2,t}\right)^{1/2}, \end{aligned} \tag{11}$$

and

$$\rho(s_t) = \rho_L \left[1 - G\left(s_t; \theta\right)\right] + \rho_H G\left(s_t; \theta\right), \tag{12}$$

where $-1 < \rho_j < 1,\ j = L, H$ denotes the correlation coefficient in the low (tranquil) and high (contagion) correlation regimes, respectively. $G(\cdot)$ is the probability/transition function of the high correlation regime, s_t is the time-dependent transition variable, and θ denotes a vector of parameters.

Following Berben and Jansen (2005), we assume that s_t is a function of time, t/T. This specification is simple, but useful in modeling an unusually high conditional correlation, ρ_H ($> \rho_L$), which may occur during a contagion period triggered by a crisis. We consider the following transition function.

$$G\left(s_t; \theta\right) = 1 - \exp\left[-\gamma^2 \left(s_t - c\right)^2\right],\ \theta = [\gamma \quad c]' \tag{13}$$

The transition function (13) is the time-dependent exponential smooth transition (EST) function. Berben and Jansen (2005) use the logistic smooth transition function, which is suitable to model a permanent regime shift. Since we are more interested in a temporary shift to ρ_H, we consider an exponential type transition function. γ determines how quickly transitions occur (smoothness) and c is a location parameter. We can estimate the unknown parameters of the EST NLCC-MGARCH model by maximizing the following log-likelihood function with respect to all parameters simultaneously.

$$\mathcal{L}= -\frac{1}{2}\sum_{t=1}^{T}\left(2\log(2\pi)+\log|\mathbf{H}_t|+\mathbf{e}_t^{\prime}\mathbf{H}_t{}^{-1}\mathbf{e}_t\right)$$

3.3 The DCCX-MGARCH Model

We now propose a novel DCC-MGARCH model where the conditional correlation coefficient is determined by exogenous variables (DCCX-MGARCH). We assume the following.

$$h_{1,2,t} = \rho(\mathbf{x}_t)\left(h_{1,1,t}h_{2,2,t}\right)^{1/2}, \tag{14}$$

where $-1 < \rho(\mathbf{x}_t) < 1$ is an monotonic increasing function of $\mathbf{x}_t$, a $k \times 1$ vector of economic fundamental variables that affect the size of the conditional correlation. This approach is useful for identifying propagation channels of potentially harmful effects of crises.

We propose the following parameterization for such a conditional correlation function.

$$\rho(\mathbf{x}_t) = 2\left[\frac{\exp\left(\theta^{\prime}\mathbf{x}_t\right)}{1+\exp\left(\theta^{\prime}\mathbf{x}_t\right)}\right] - 1, \tag{15}$$

where $\theta = [\theta_1\ \theta_2\ \cdots\ \theta_k]^{\prime}$ and $\mathbf{x}_t = [x_{1,t}\ x_{2,t}\ \cdots\ x_{k,t}]^{\prime}$.

4 Empirical Results

4.1 Data and Summary Statistics

We utilize daily observations of stock indices and foreign exchange rates obtained from Bloomberg. The sample period is April 2, 2007 to August 31, 2009. Exchange rates are national currency prices of the US dollar. Asset returns are calculated by taking two-day differentials of natural logarithm asset prices, multiplied by 100. We study the dynamic conditional correlations between daily returns of the S&P500 index and national equity returns, as well as between the Euro-US dollar exchange rate returns and foreign exchange rate returns of national currencies relative to US dollars for five emerging Asian countries: Indonesia (IN), Korea (KR), the Philippines (PH), Thailand (TH), and Taiwan (TW).

We first note strong co-movement phenomena in equity prices (see Figure 1) and in foreign exchange rates (see Figure 2) during our sample period. Especially, all national equity prices fell substantially around the collapse of Lehman Brothers in September 2008. Similarly, abrupt depreciations of most currencies against dollars were observed during the Lehman episode with exceptions of the Philippines and Taiwan. It should be also noted that the GARCH volatility substantially rose around the Lehman failure for all equity returns and for three exchange rates, the Euro, the Indonesian Ruphia, and the Korean Won.

Figures 1 and 2 about here

We report some preliminary summary statistics of our baseline data in Table 1. The mean value of the US equity returns was the lowest, while Indonesia's average equity return was the highest. With exceptions of Indonesia and Korea, all countries experienced negative returns on average during the sample period. Also, on average, the US dollar lost its values against the Euro, the Thailand Baht, and the Taiwan Dollar, while gained value against other currencies.

Table 1 about here

For the variables that determine conditional correlations of asset returns, we use daily amounts of the buy and sell equity order flows by foreign investors, the sovereign CDS premium, the VIX index, the TED spread, and the Libor-overnight index swap (OIS) spread.[7] The fundamental variables that determine the size of DCC are briefly discussed below.

One motivation of using the amount of foreign order flows in local stock markets is an observation of high dependence of local stock markets in the emerging Asian countries on the trade patterns of foreign investors. We use the total amount of the buy- and sell-order by foreign investors instead of their net order flows, because the total amount should better proxy the degree of financial linkages between countries.

We also employ the sovereign CDS premium, costs of insuring against a sovereign default, as a measure of country risk of emerging Asian economies. The sovereign CDS premium of these 5 countries soared beginning in September 2008.

The VIX index, the Chicago Board Options Exchange (CBOE) volatility index, is used as a proxy for market uncertainty. It is a widely used barometer of investor fear.[8] The TED spread is used as a measure for the level of financial stress in the interbank market. The TED spread is the difference between the three-month LIBOR and the yield on the US Treasury bills with same maturity.[9]

The Libor-OIS spread is a measure of the market-wide liquidity risk. Adrian and Shin (2008) point out that aggregate liquidity can be understood as the rate of growth of the aggregate financial-sector balance sheet. A fall of asset prices during the crisis makes banks reluctant to lend in the interbank market. This would reduce market liquidity and require a higher risk premium for longer maturity loans. The spread between the term and overnight interbank lending, then, would rise reflecting banks' reluctance to extend longer maturity loans. The Libor-OIS spreads increased

[7] Similarly, Eichengreen *et al.* (2009) use the VIX index, the TED spread, and the dlloar LIBOR-OIS spread. Frank and Hesse (2009) use the Libor-OIS spread as a measure for bank funding liquidity and for a general stress level in the interbank money market. Gonzalez-Hermosillo and Hesse (2009) use the VIX index and the TED spread as proxy variables for global financial market condition. Melvin and Taylor (2009) employ the TED spread to measure the credit risk of the banking sector.

[8] The VIX index is a volatility index implied by the current prices of options on the S&P 500 index. It represents expected future stock market volatility over the next 30 days.

[9] Eichengreen *et al.* (2009) point out that the TED spread reflects not just banking sector credit risk but also includes liquidity or flight-to-quality risk since it can be decomposed into the banking sector credit risk premium (LIBOR-OIS) and liquidity or flight-to-quality premium (OIS-T-Bill). The TED spread rose sharply in the post-Lehman crash period due to a substantial increase in credit risk (the LIBOR-OIS spread) instead of the rise in the liquidity premium (the OIS-T-Bill differential).

substantially after the collapse of Lehman Brothers in September 2008. We omit summary statistics for these variables to save space.

4.2 Estimation Results

We first present a conventional diagonal BEKK-MGARCH (Engle and Kroner, 1995) estimation results in Table 2 as a benchmark. We also implement DCC-MGARCH along with CCC-MGARCH estimations (Tables 3 and 4) and compare the estimated dynamic conditional correlations with those from the BEKK-MGARCH model. See Figures 3 through 5. The dashed vertical line indicates September 15, 2008 when financial market instability culminated after the failure of Lehman Brothers.

Estimated conditional correlations by the DCC-MGARCH and the BEKK-MGARCH are overall similar. However, the BEKK estimates tend to exhibit higher variability covering a wider range of estimates. For instance, the conditional correlation of the equity returns between Indonesia and the US ranges between about -0.2 to 0.8 when the BEKK method is applied, while about 0.2 to 0.55 when we use the DCC-MGARCH method. Overall, the estimates from both models strongly imply that the notion of possible de-coupling has been misplaced in the case of emerging Asian financial markets (Dooley and Hutchison, 2009).

One notable finding is the following. For the equity returns, the correlation coefficient estimates rose substantially around the Lehman episode with an exception of Thailand. However, unusually high correlations were short-lived as they quickly moved back to previous lower levels in around October 2008. Similar movements around the Lehman episode were observed for the exchange rate changes. Spikes in the correlation of exchange rates are more pronounced than in the case of stock prices. We also observe similar spikes across local markets.

Naturally, the CCC estimates are about the mean values of the DCC estimates. We implement a test for the null hypothesis of the CCC against the DCC alternative (Engle and Sheppard, 2001). The results overall accept the null hypothesis with 47.5% and 20.2% p-values for the stock market and the foreign exchange market, respectively. One shouldn't be surprised to see this because our observations cover only 29 months and sudden elevation of the conditional correlations persist only for a month. Under such circumstances, it is not an easy task to find statistical evidence of such sudden changes in conditional correlations. Put different, the power of such tests may not be good.

Tables 2, 3, and 4 about here

Figures 3, 4, and 5 about here

These findings suggest a possibility of nonlinear movements of correlation coefficients. To empirically investigate this possibility, we implement NLCC-MGARCH estimations with the exponential smooth transition function between the tranquil period correlation (ρ_L) and the contagion period correlation (ρ_H). The parameter estimates are reported in Tables 5 and 6. See Figure 6 for the conditional correlation estimates of these models.

The results are overall consistent with our previous findings. With an exception of Thailand equity returns, estimated conditional correlations rapidly rise to the contagion regime around the Lehman episode period. It should be noted that the ρ_H estimates are substantially different from the ρ_L estimates. In the case of Indonesia, for example, the equity correlation estimate increased from about 0.363 to 0.836 and the exchange rate correlation moved from 0.137 to 0.536. Similar findings were observed for the rest of the countries with an exception of Thailand equity returns. We also note that smoothness parameter estimates of the EST model are quite large, implying regime shifts occur fairly abruptly. This provides additional evidence for the existence of contagion triggered by unexpected news shocks. We also note that estimated durations of the contagion period are fairly short.

In a nutshell, our results imply that the US financial crisis had a strong spillover effect on financial asset returns in most emerging Asian countries when the news of Lehman Brothers failure was revealed in September 2008.

Tables 5 and 6 about here

Figure 6 about here

Next, we turn to analysis on determinant factors of the conditional correlation coefficient by the DCCX-MGARCH model. A number of variables can be considered for the factors that play important roles for determining the size of the dynamic conditional correlation. We first choose the factors that are related to the financial condition of the *source* country where the crisis originated. We consider the VIX index as a US financial market stability measure, and the TED spread and the dollar Libor-OIS spread as the US risk premium or liquidity availability measures. We expect these financial instability/fragility measures of the source country to have positive effects on the conditional correlation. Second, we consider the sovereign CDS premium as a measure of potential financial fragility in emerging Asian countries, which may increase likelihood of spillover effects. Thirdly, we also consider the amount of foreign buy- and sell-order flows as an exogenous factor in local stock markets. Sudden drainage of foreign capital (flight to safety) may cause severe liquidity crunch, which may increase odds of contagion.

We report our parameter estimation results in Tables 9 and 10. Conditional correlation estimates appear in Figure 7. Our major findings are as follows.

First, for the equity returns, foreign capital has a significantly positive effect on conditional correlations in all five countries. The Libor-OIS spread has an insignificant effect for all countries. The sovereign CDS premium has a significant effect on the correlations in Indonesia and Philippines, though with a negative sign. For those two countries, the VIX index has a significantly positive effect, implying that uncertainty in the US stock market may spread to those countries. Based on these findings, we believe that the spillover effect of the US stock market shocks is mainly due to surges in foreign capital and propagations of US uncertainty to some emerging Asian countries. Global liquidity conditions seem to have an insignificant effect. Given the interconnectedness of global financial markets, investors' increase in global risk aversion triggered by problems in advanced economies rapidly spilled over into emerging countries, as funds were pulled out from the latter and subsequently invested into the safest and most liquid assets such as mature market fixed income securities (Frank and Hesse, 2009).

Our findings on stock markets are similar to those of Didier *et al.* (2010). In their study that analyzes the driving factors of the co-movement between US stock returns and returns in 83 countries, they also find that a larger share of US investors' asset holdings in foreign markets is associated with a more pronounced reaction to the US crisis.[10]

Second, the Libor-OIS spread, the sovereign CDS premium, and foreign capital appear to have overall positive effects on conditional correlations with an exception of Korea for the CDS premium. Especially, the amount of foreign buy- and sell-trades has a significantly positive effect on 3 out of 5 countries. Although the TED spread appears to have a significant effect on Korea, the Philippines, and Taiwan, it comes with a negative sign for all five countries, which lacks economically meaningful interpretations. Overall, it seems that the Libor-OIS spread, the sovereign CDS premium, and foreign capital play important roles for determining conditional correlations in international foreign exchange markets.[11] The results on exchange rates seem consistent with arguments that the current global crisis spreads quickly to other countries, first through lack of available liquidity and then through concerns on solvency and loss of confidence.

These findings are consistent with Fratzscher's (2009) explanations on exchange rate movements during financial crises. He points out that a sharp reversal in the pattern of global capital flows played a seminal role for global foreign exchange rate movements. He concludes that a repatriation of capital to the US by US investors, a flight-to-safety phenomenon by US and non-US investors, an increased need for US dollar liquidity and an unwinding of carry trade positions may all have played a role in the sharp appreciation trend of the US dollar.

Third, Figure 7 clearly illustrate substantial and abrupt changes in dynamic conditional correlations during the Lehman Brothers episode, which, we believe, imply our DCCX-MGARCH model is a useful tool in studying spillover effects of financial crises.

[10] Didier *et al.* (2010) point out that their finding is consistent with a "margin calls" story. Facing large capital losses at home, US investors withdrew money from foreign investments, which leads to a substantial effect especially on countries where the share of foreign investments by the US is larger.

[11] Frank and Hesse (2009) also report the important role of the dollar Libor-OIS spread for channelling adverse shocks to other countries. They find that correlations between the US Libor-OIS spread and the EMBI+ sovereign bonds spreads of Asia sharply increase following the onset of the subprime crisis.

Tables 7 and 8 about here

Figure 7 about here

5 Concluding Remarks

The present paper uses an array of MGARCH models to estimate dynamic conditional correlations of financial asset returns between the US and five emerging Asian countries. Our major findings imply that the recent US financial crisis, triggered by the collapse of Lehman Brothers in September 2008, has a substantial spillover effect on emerging Asian countries. Our analysis shows that the conditional correlation, overall, abruptly rose to a much higher level around the Lehman Brothers failure period and such a high correlation has persisted for a fairly short period of time. Put differently, we find short-lived but non-negligible financial contagion from the US to emerging Asian countries.

We also investigate major factors that determine the size of conditional correlations using a novel DCCX-MGARCH model. Especially, we find a substantial role of the foreign investors for co-movements across international equity markets. In the foreign exchange markets, the dollar Libor-OIS spread, the sovereign CDS premium, and the amount of foreign order flows have significant effects on determining dynamic conditional correlations.

Our analysis provides the following policy implications. Our NLCC-MGARCH model estimations imply that spillover effects of the US financial crisis occurred abruptly. Though financial contagion seems to persist for a fairly short period of time, its impacts can be substantial and potentially harmful to these countries. This implies that emerging Asian countries are quite vulnerable to external shocks and can experience a sudden acceleration of systemic risk through deterioration in both the capital and the foreign exchange markets. This possibility calls for a need to construct a financial stabilization mechanism against contagion originating from other countries.

It also appears that foreign investors play a potentially important role in channeling foreign crises to domestic economies. Therefore, emerging countries should make an effort to lessen this effect, possibly by supporting the role of domestic institutional investors in terms of total transaction volumes in these financial markets.

Lastly, we find a stronger spillover effect in the foreign exchange market than the equity market. Given the importance of trade accounts in these emerging Asian economies, foreign exchange market instability caused by external shocks may lead to a serious dollar liquidity problem even when their economic fundamentals are healthy. Therefore, it is advised for these countries to equip institutional arrangements to enhance international cooperation, such as currency swap agreements.

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Table 1. Summary Statistics

	Stock Price Returns					
	USA	IN	KR	PH	TH	TW
Mean	−0.00055	0.00040	0.00015	−0.00020	−0.00025	−0.00007
Median	0.00080	0.00177	0.00190	0.00056	0.00116	0.00015
Maximum	0.10246	0.07623	0.11284	0.07056	0.08054	0.07549
Minimum	−0.09470	−0.10954	−0.11172	−0.13089	−0.06735	−0.11090
Std. Dev.	0.01980	0.02053	0.02038	0.01809	0.01880	0.01717
Skewness	−0.32679	−0.52421	−0.49231	−0.97701	−0.05700	−0.52263
Kurtosis	7.27123	7.17861	7.88882	9.17514	4.81961	8.04300
	Foreign Exchange Rate Returns					
	Euro	IN	KR	PH	TH	TW
Mean	−0.00012	0.00017	0.00049	0.00002	−0.00001	−0.00005
Median	−0.00031	−0.00005	0.00022	−0.00002	0.00008	0.00000
Maximum	0.06261	0.05356	0.10693	0.01703	0.01648	0.01237
Minimum	−0.04607	−0.05557	−0.13594	−0.02057	−0.01721	−0.01097
Std. Dev.	0.00817	0.00998	0.01493	0.00518	0.00339	0.00271
Skewness	0.34312	0.36868	−1.01083	−0.03472	−0.10003	0.09355
Kurtosis	12.2979	11.1303	25.5979	3.50013	8.06536	5.92453

Table 2. Diagonal BEKK-MGARCH Model

$$\mathbf{H}_t = \mathbf{M} + \mathbf{A}'\mathbf{e}'_{t-1}\mathbf{e}_{t-1}\mathbf{A} + \mathbf{B}\mathbf{H}_{t-1}\mathbf{B}'$$

$$\mathbf{M} = \begin{bmatrix} \omega_1 & \omega_2 \\ \omega_2 & \omega_3 \end{bmatrix}, \ \mathbf{A} = \begin{bmatrix} \alpha_1 & 0 \\ 0 & \alpha_2 \end{bmatrix}, \ \mathbf{B} = \begin{bmatrix} \beta_1 & 0 \\ 0 & \beta_2 \end{bmatrix}$$

	Stock Price Returns				
	IN	KR	PH	TH	TW
ω_1	0.1963* (0.0000)	0.2158* (0.0000)	0.2136* (0.0000)	0.2204* (0.0000)	0.1939* (0.0000)
ω_2	0.3184* (0.0000)	0.1463* (0.0000)	0.3084* (0.0000)	0.1154* (0.0000)	0.1102* (0.0000)
ω_3	0.3486* (0.0000)	0.2658* (0.0000)	0.3718* (0.0000)	0.2067* (0.0000)	0.2631* (0.0000)
α_1	0.3027* (0.0000)	0.3023* (0.0000)	0.2882* (0.0000)	0.3323* (0.0000)	0.2904* (0.0000)
α_2	0.4042* (0.0000)	0.3053* (0.0000)	0.2996* (0.0000)	0.2253* (0.0000)	0.3136* (0.0000)
β_1	0.9500* (0.0000)	0.9468* (0.0000)	0.9495* (0.0000)	0.9378* (0.0000)	0.9524* (0.0000)
β_2	0.8909* (0.0000)	0.9417* (0.0000)	0.9101* (0.0000)	0.9673* (0.0000)	0.9374* (0.0000)
$-\ln L$	2207.2	2182.2	2085.5	2193.0	2129.5
	Foreign Exchange Rate Returns				
	IN	KR	PH	TH	TW
ω_1	0.0350* (0.0000)	0.0658* (0.0000)	0.0468* (0.0000)	0.0457* (0.0000)	0.0435* (0.0000)
ω_2	0.0314* (0.0000)	0.1230* (0.0000)	0.0585* (0.0000)	0.0033* (0.0000)	−0.0003* (0.0015)
ω_3	0.1010* (0.0000)	0.0000 (0.9940)	0.1195* (0.0000)	0.0330* (0.0000)	0.0228* (0.0000)
α_1	0.2438* (0.0000)	0.2678* (0.0000)	0.2568* (0.0000)	0.2694* (0.0000)	0.2793* (0.0000)
α_2	0.4229* (0.0000)	0.7023* (0.0000)	0.2244* (0.0000)	0.3221* (0.0000)	0.3872* (0.0000)
β_1	0.9729* (0.0000)	0.9631* (0.0000)	0.9678* (0.0000)	0.9661* (0.0000)	0.9651* (0.0000)
β_2	0.9097* (0.0000)	0.7861* (0.0000)	0.9403* (0.0000)	0.9468* (0.0000)	0.9297* (0.0000)
$-\ln L$	1220.2	1249.5	1017.4	683.34	535.64

Note: i) p-values are reported in parentheses. ii) * indicates statistical significance at the 5% level.

Table 3. CCC- and DCC-MGARCH Model: Stock Price Returns

$$GARCH : h_{i,i,t} = \omega_i + \alpha_i e^2_{i,t-1} + \beta_i h_{i,i,t-1}$$
$$CCC : H_t = D_t R D_t,\ D_t = diag\left[\sqrt{h_{i,i,t}}\right],\ R = [\rho_{i,j}]$$
$$DCC : Q_t = S(1-\alpha-\beta) + \alpha\left(\varepsilon_{t-1}\varepsilon'_{t-1}\right) + \beta Q_{t-1}$$

		US	IN	KR	PH	TH	TW
$GARCH$	ω_i	0.0689* (0.0000)	0.1807* (0.0000)	0.1263* (0.0000)	0.2112* (0.0000)	0.0869* (0.0000)	0.1144* (0.0000)
	α_i	0.1312* (0.0000)	0.1767* (0.0000)	0.1162* (0.0000)	0.1196* (0.0000)	0.1265* (0.0000)	0.1835* (0.0000)
	β_i	0.8502* (0.0000)	0.7885* (0.0000)	0.8516* (0.0000)	0.8065* (0.0000)	0.8601* (0.0000)	0.7916* (0.0000)
CCC	$\rho_{1,j}$	–	0.3747* (0.0000)	0.4174* (0.0000)	0.5116* (0.0000)	0.3715* (0.0000)	0.3424* (0.0000)
	$\rho_{2,j}$	–	–	0.5816* (0.0000)	0.4418* (0.0000)	0.5038* (0.0000)	0.5853* (0.0000)
	$\rho_{3,j}$	–	–	–	0.4480* (0.0000)	0.7069* (0.0000)	0.5441* (0.0000)
	$\rho_{4,j}$	–	–	–	–	0.4631* (0.0000)	0.4285* (0.0000)
	$\rho_{5,j}$	–	–	–	–	–	0.4671* (0.0000)
	$-\ln L$	6027.0					
DCC	α	0.0298* (0.0000)					
	β	0.7844* (0.0000)					
	$-\ln L$	6015.3					

Note: i) p-values are reported in parentheses. ii) * indicates statistical significance at the 5% level.

Table 4. CCC- and DCC-MGARCH Model: Foreign Exchange Rate Returns

$$GARCH: h_{i,i,t} = \omega_i + \alpha_i e_{i,t-1}^2 + \beta_i h_{i,i,t-1}$$
$$CCC: H_t = D_t R D_t,\ D_t = diag\left[\sqrt{h_{i,i,t}}\right],\ R = [\rho_{i,j}]$$
$$DCC: Q_t = S(1-\alpha-\beta) + \alpha\left(\varepsilon_{t-1}\varepsilon_{t-1}^{'}\right) + \beta Q_{t-1}$$

		Euro	IN	KR	PH	TH	TW
$GARCH$	ω_i	0.0024* (0.0000)	0.0103* (0.0000)	0.0121* (0.0000)	0.0072* (0.0000)	0.0007* (0.0000)	0.0009* (0.0000)
	α_i	0.0651* (0.0000)	0.1704* (0.0000)	0.2737* (0.0000)	0.0399* (0.0000)	0.0846* (0.0000)	0.1714* (0.0000)
	β_i	0.9349* (0.0000)	0.8296* (0.0000)	0.7263* (0.0000)	0.9338* (0.0000)	0.9150* (0.0000)	0.8286* (0.0000)
CCC	$\rho_{1,j}$	–	0.1674* (0.0000)	0.3023* (0.0000)	0.2842* (0.0000)	0.2968* (0.0000)	0.3144* (0.0000)
	$\rho_{2,j}$	–	–	0.3452* (0.0000)	0.3816* (0.0000)	0.2219* (0.0000)	0.1771* (0.0000)
	$\rho_{3,j}$	–	–	–	0.3865* (0.0000)	0.3649* (0.0000)	0.2286* (0.0000)
	$\rho_{4,j}$	–	–	–	–	0.3038* (0.0000)	0.2520* (0.0000)
	$\rho_{5,j}$	–	–	–	–	–	0.1947* (0.0000)
	$-\ln L$	2123.1					
DCC	α	0.0217* (0.0000)					
	β	0.8543* (0.0000)					
	$-\ln L$	2113.7					

Note: i) p-values are reported in parentheses. ii) * indicates statistical significance at the 5% level.

Table 5. EST NLCC-MGARCH Model: Stock Price Returns

$$h_{1,1,t} = \omega_1 + \alpha_1 e_{1,t-1}^2 + \beta_1 h_{1,1,t-1}$$
$$h_{2,2,t} = \omega_2 + \alpha_2 e_{2,t-1}^2 + \beta_2 h_{2,2,t-1}$$
$$h_{1,2,t} = \rho(s_t)\left(h_{1,1,t} h_{2,2,t}\right)^{1/2}$$
$$\rho(s_t) = \rho_L\left[1 - G\left(s_t;\theta\right)\right] + \rho_H G\left(s_t;\theta\right)$$
$$G\left(s_t;\theta\right) = 1 - \exp\left[-\gamma^2\left(s_t - c\right)^2\right],\ \theta = [\gamma \quad c]'$$

	Variance Equation				
	IN	KR	PH	TH	TW
ω_1	0.0397* (0.037)	0.0342* (0.032)	0.0322* (0.045)	0.0389* (0.030)	0.03319 (0.077)
ω_2	0.1799* (0.005)	0.0774* (0.023)	0.3282* (0.002)	0.0668* (0.036)	0.0568 (0.053)
α_1	0.1148* (0.000)	0.1055* (0.000)	0.0986* (0.000)	0.1057* (0.000)	0.1048* (0.000)
α_2	0.1823* (0.000)	0.0913* (0.000)	0.1645* (0.000)	0.1409* (0.000)	0.0970* (0.000)
β_1	0.8741* (0.000)	0.8880* (0.000)	0.8933* (0.000)	0.8847* (0.000)	0.8891* (0.000)
β_2	0.7867* (0.000)	0.8895* (0.000)	0.7283* (0.000)	0.8449* (0.000)	0.8945* (0.000)
	Correlation Coefficient Equation				
	IN	KR	PH	TH	TW
ρ_L	0.3625* (0.000)	0.4386* (0.000)	0.5587* (0.000)	0.3494* (0.000)	0.3993* (0.000)
ρ_H	0.8364* (0.000)	0.7585* (0.000)	0.8723* (0.000)	0.4414* (0.002)	0.6002* (0.000)
γ	175.20* (0.024)	163.09 (0.193)	62.462* (0.022)	23.834 (0.253)	50.000 (0.852)
c	0.6277* (0.000)	0.6278* (0.000)	0.6779* (0.000)	0.5823* (0.000)	0.6348* (0.001)
$-\log L$	2201.04	2168.89	2079.43	2107.27	2192.25

Note: i) p-values are reported in parentheses. ii) * indicates statistical significance at the 5% level.

Table 6. EST NLCC-MGARCH Model: Foreign Exchange Rate Returns

$$h_{1,1,t} = \omega_1 + \alpha_1 e_{1,t-1}^2 + \beta_1 h_{1,1,t-1}$$
$$h_{2,2,t} = \omega_2 + \alpha_2 e_{2,t-1}^2 + \beta_2 h_{2,2,t-1}$$
$$h_{1,2,t} = \rho(s_t) \left(h_{1,1,t} h_{2,2,t}\right)^{1/2}$$
$$\rho(s_t) = \rho_L \left[1 - G\left(s_t; \theta\right)\right] + \rho_H G\left(s_t; \theta\right)$$
$$G\left(s_t; \theta\right) = 1 - \exp\left[-\gamma^2 \left(s_t - c\right)^2\right], \ \theta = [\gamma \ \ c]'$$

	Variance Equation				
	IN	KR	PH	TH	TW
ω_1	0.0020 (0.267)	0.0019 (0.235)	0.0016 (0.317)	0.0017 (0.201)	0.0018 (0.164)
ω_2	0.0083* (0.011)	0.0055* (0.039)	0.0096 (0.199)	0.0014* (0.025)	0.0008* (0.046)
α_1	0.0726* (0.000)	0.0694* (0.000)	0.0754* (0.000)	0.0745* (0.000)	0.0732* (0.000)
α_2	0.2777* (0.000)	0.2513* (0.000)	0.0510* (0.031)	0.3178* (0.000)	0.0959* (0.000)
β_1	0.9233* (0.000)	0.9345* (0.000)	0.9304* (0.000)	0.9210* (0.000)	0.9303* (0.000)
β_2	0.7675* (0.000)	0.7442* (0.000)	0.9136* (0.000)	0.6849* (0.000)	0.9044* (0.000)
	Correlation Coefficient Equation				
	IN	KR	PH	TH	TW
ρ_L	0.1365* (0.005)	0.3081* (0.000)	0.2362* (0.000)	0.2996* (0.000)	0.2879* (0.000)
ρ_H	0.5358* (0.000)	0.8249* (0.000)	0.4906* (0.000)	0.5536* (0.000)	0.9002* (0.000)
γ	22.898* (0.025)	49.200* (0.001)	11.676* (0.008)	31.786* (0.021)	185.96 (0.170)
c	0.5620* (0.000)	0.6250* (0.000)	0.6936* (0.000)	0.6278* (0.000)	0.6435* (0.000)
$-\log L$	1190.28	1234.09	1017.08	525.82	677.52

Note: i) p-values are reported in parentheses. ii) * indicates statistical significance at the 5% level.

Table 7. DCCX-MGARCH Model: Stock Price Returns

$$h_{1,1,t} = \omega_1 + \alpha_1 e_{1,t-1}^2 + \beta_1 h_{1,1,t-1}$$
$$h_{2,2,t} = \omega_2 + \alpha_2 e_{2,t-1}^2 + \beta_2 h_{2,2,t-1}$$
$$h_{1,2,t} = \rho(\mathbf{x}_t)\left(h_{1,1,t} h_{2,2,t}\right)^{1/2}$$
$$\rho(\mathbf{x}_t) = 2\left[\frac{\exp\left(\theta'\mathbf{x}_t\right)}{1+\exp\left(\theta'\mathbf{x}_t\right)}\right] - 1,\ \theta = \left[\theta_1\ \theta_2\ \cdots\ \theta_k\right]'$$

	Variance Equation				
	IN	KR	PH	TH	TW
ω_1	0.0392* (0.032)	0.0445* (0.018)	0.0346* (0.045)	0.0439* (0.025)	0.0357 (0.060)
ω_2	0.1943* (0.004)	0.0931* (0.019)	0.3518* (0.001)	0.0805* (0.025)	0.0648* (0.045)
α_1	0.1247* (0.000)	0.1039* (0.000)	0.1010* (0.000)	0.1016* (0.000)	0.1057* (0.000)
α_2	0.1857* (0.000)	0.0903* (0.000)	0.1601* (0.000)	0.1410* (0.000)	0.0966* (0.000)
β_1	0.8682* (0.000)	0.8835* (0.000)	0.8902* (0.000)	0.8861* (0.000)	0.8864* (0.000)
β_2	0.7787* (0.000)	0.8853* (0.000)	0.7233* (0.000)	0.8390* (0.000)	0.8914* (0.000)
	Correlation Coefficient Equation				
	IN	KR	PH	TH	TW
θ_1	0.1055* (0.045)	0.1299* (0.000)	0.1815* (0.003)	0.1875* (0.008)	0.1671* (0.023)
θ_2	−0.8744* (0.014)	−0.1357 (0.281)	−0.4560* (0.014)	0.1316 (0.708)	−0.0871 (0.405)
θ_3	1.2683* (0.027)	−0.1086 (0.361)	0.7900* (0.006)	−0.4824 (0.388)	−0.0296 (0.889)
θ_4	−0.0331 (0.799)	0.0646 (0.502)	−0.0583 (0.559)	0.0790 (0.694)	0.1466 (0.370)
$-\log L$	2201.35	2168.06	2078.90	2105.88	2192.67

Note: i) x_1, x_2, x_3, x_4 are the foreign investment, the sovereign CDS premium, the VIX index, and the dollar Libor-OIS spread, respectively. ii) p-values are reported in parentheses. iii) * indicates statistical significance at the 5% level.

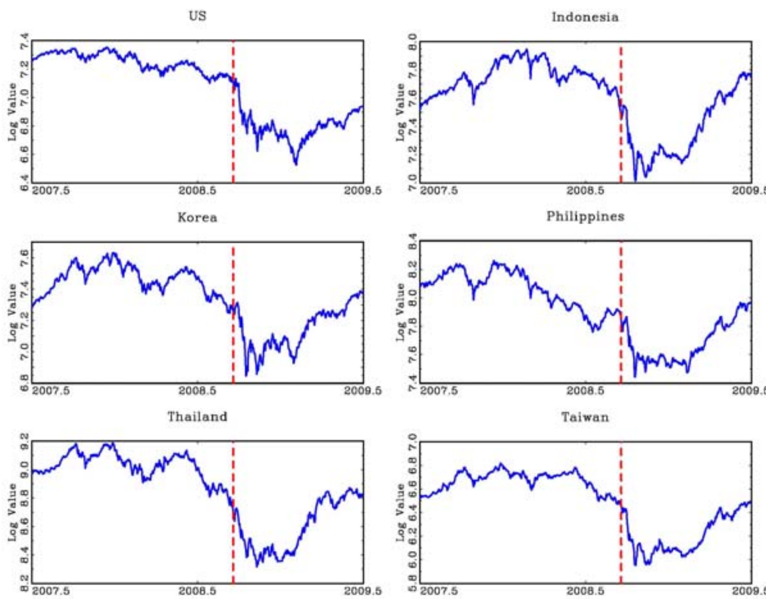
Table 8. DCCX-MGARCH Model: Foreign Exchange Rate Returns

$$h_{1,1,t} = \omega_1 + \alpha_1 e_{1,t-1}^2 + \beta_1 h_{1,1,t-1}$$
$$h_{2,2,t} = \omega_2 + \alpha_2 e_{2,t-1}^2 + \beta_2 h_{2,2,t-1}$$
$$h_{1,2,t} = \rho(\mathbf{x}_t)\,(h_{1,1,t}h_{2,2,t})^{1/2}$$
$$\rho(\mathbf{x}_t) = 2\left[\frac{\exp\left(\theta'\mathbf{x}_t\right)}{1+\exp\left(\theta'\mathbf{x}_t\right)}\right] - 1,\ \ \theta = [\theta_1\ \theta_2\ \cdots\ \theta_k]'$$

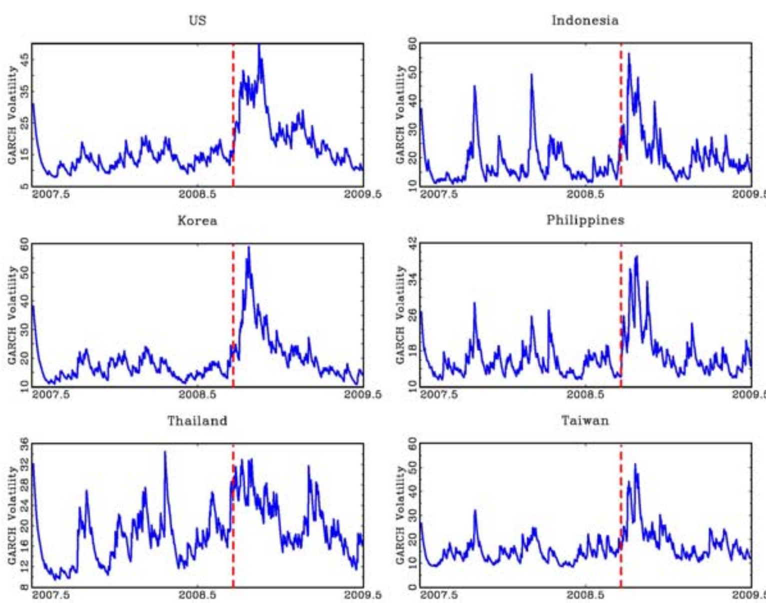
	IN	KR	PH	TH	TW
			Variance Equation		
ω_1	0.0020 (0.256)	0.0027 (0.132)	0.0013 (0.382)	0.0018 (0.296)	0.0019 (0.273)
ω_2	0.0079* (0.015)	0.0078* (0.018)	0.0113 (0.232)	0.0014* (0.031)	0.0008 (0.068)
α_1	0.0805* (0.000)	0.0657* (0.000)	0.0684* (0.000)	0.0764* (0.000)	0.0739* (0.000)
α_2	0.2843* (0.000)	0.2474* (0.000)	0.0494* (0.000)	0.3064* (0.000)	0.0986* (0.000)
β_1	0.9249* (0.000)	0.9356* (0.000)	0.9375* (0.000)	0.9291* (0.000)	0.9310* (0.000)
β_2	0.7654* (0.000)	0.7195* (0.000)	0.9093* (0.000)	0.6959* (0.000)	0.9019* (0.000)
			Correlation Coefficient Equation		
	IN	KR	PH	TH	TW
θ_1	0.0584 (0.231)	0.3180* (0.000)	0.0950 (0.533)	0.0392 (0.794)	0.2624* (0.039)
θ_2	0.2915 (0.292)	−0.2913* (0.010)	0.4338* (0.002)	0.3725* (0.010)	0.2729* (0.003)
θ_3	−0.7009 (0.350)	−0.7527* (0.002)	−0.5273* (0.015)	−0.3638 (0.208)	−0.6347* (0.004)
θ_4	0.2338* (0.039)	1.0111* (0.000)	0.3834* (0.034)	0.3057 (0.470)	0.5569* (0.038)
$-\log L$	1192.33	1231.80	1015.54	522.93	671.64

Note: i) x_1, x_2, x_3, x_4 are the foreign investment, the sovereign CDS premium, the TED spread, and the dollar Libor-OIS spread, respectively. ii) p-values are reported in parentheses. iii) * indicates statistical significance at the 5% level.

Figure 1. Stock Price Data and GARCH Volatility Estimates



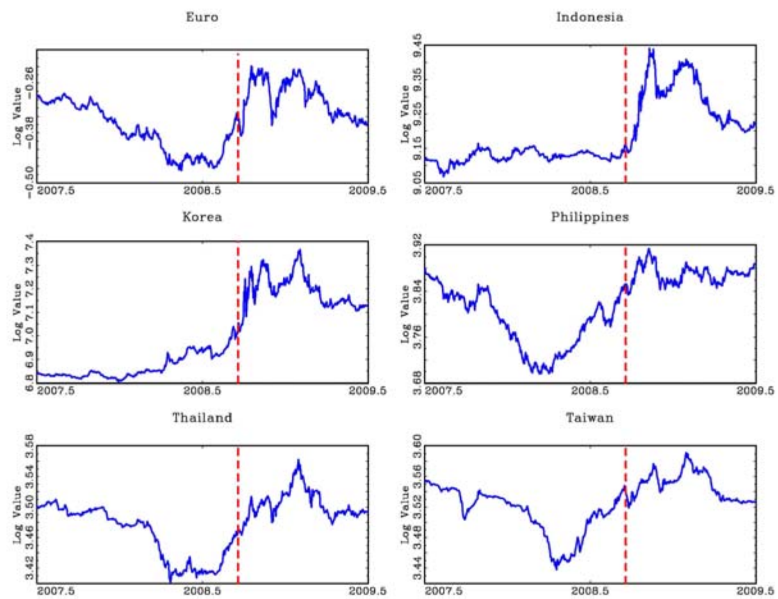
(a) Stock Price



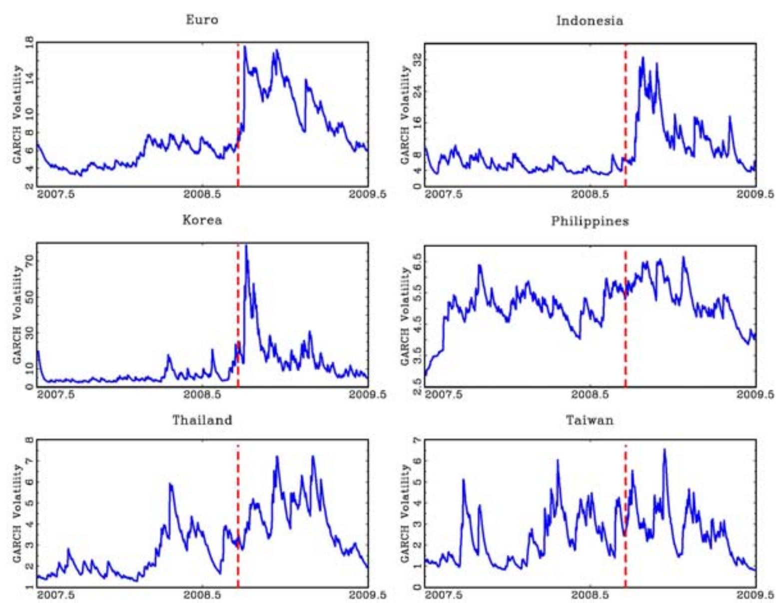
(b) GARCH Volatility Estimate

Note: The dashed vertical line indicates the Lehman failure on September 15, 2008.

Figure 2. Foreign Exchange Rate Data and GARCH Volatility Estimates



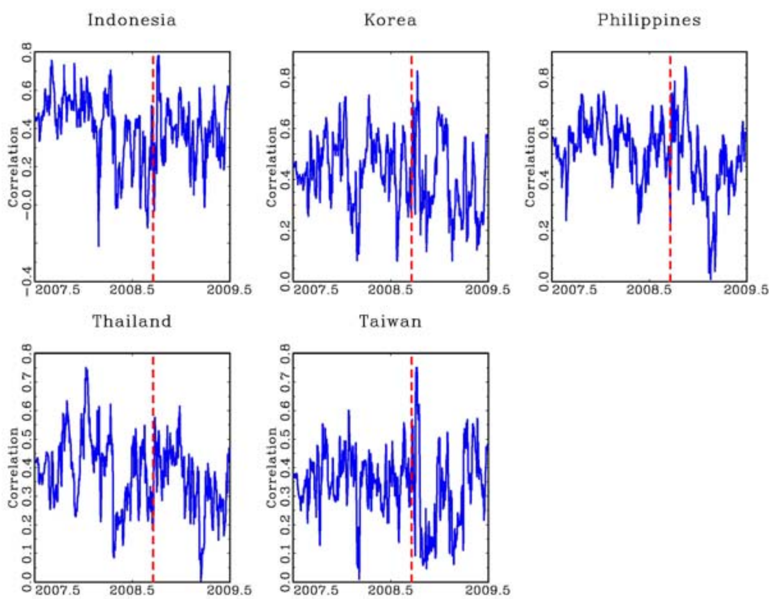
(a) Foreign Exchange Rate



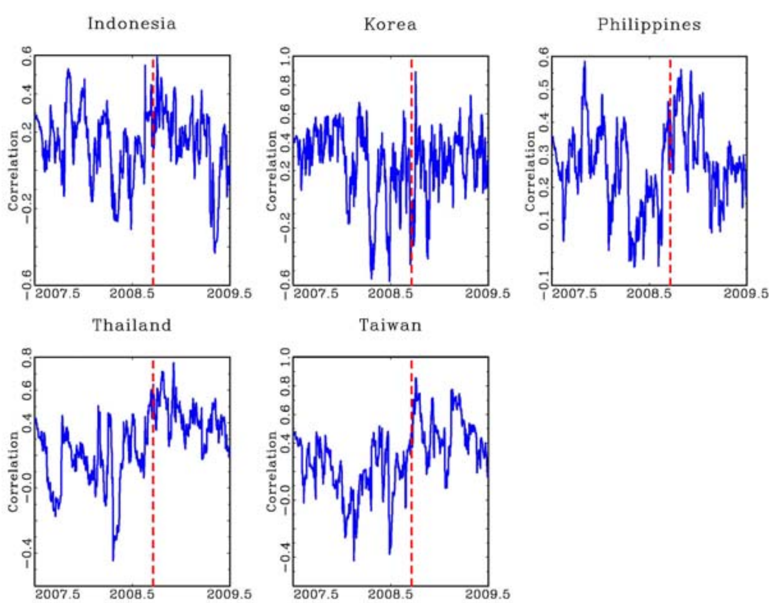
(b) GARCH Volatility Estimate

Note: The dashed vertical line indicates the Lehman failure on September 15, 2008.

Figure 3. BEKK Conditional Correlation Estimates



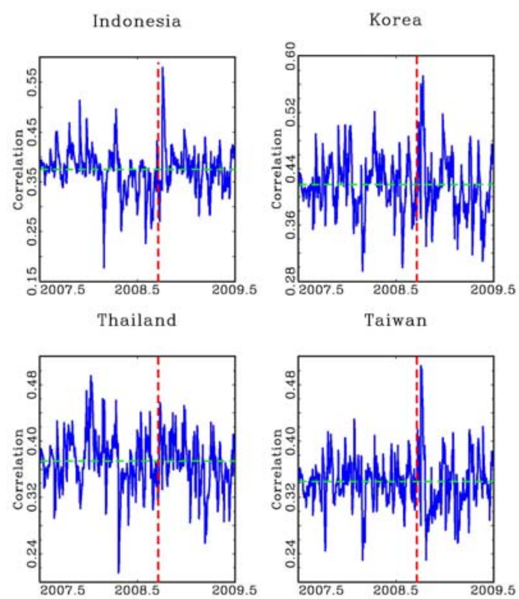
(a) Stock Price Returns



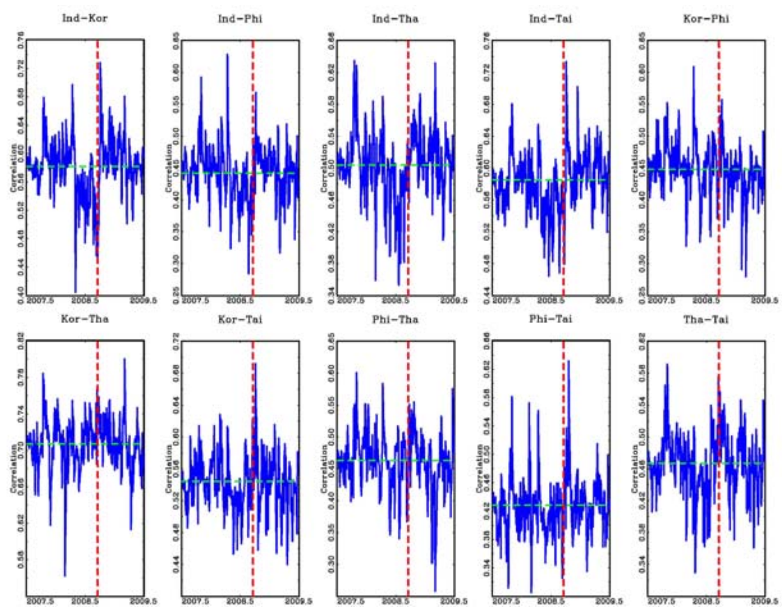
(b) Foreign Exchange Rate Returns

Note: The dashed vertical line indicates the Lehman failure on September 15, 2008.

Figure 4. DCC and CCC Estimates: Stock Price Returns



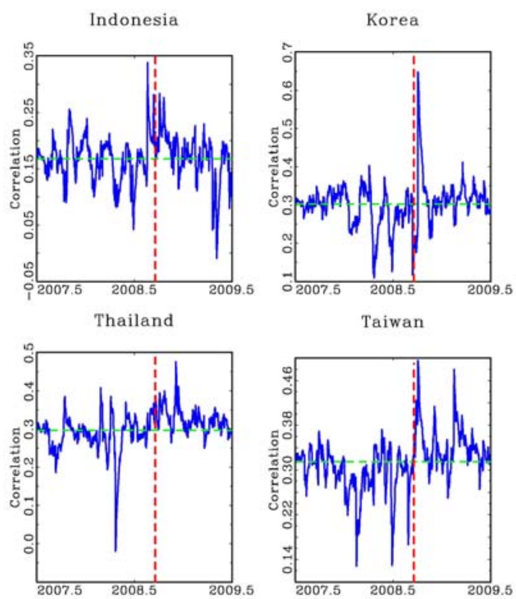
(a) With the US Stock Returns



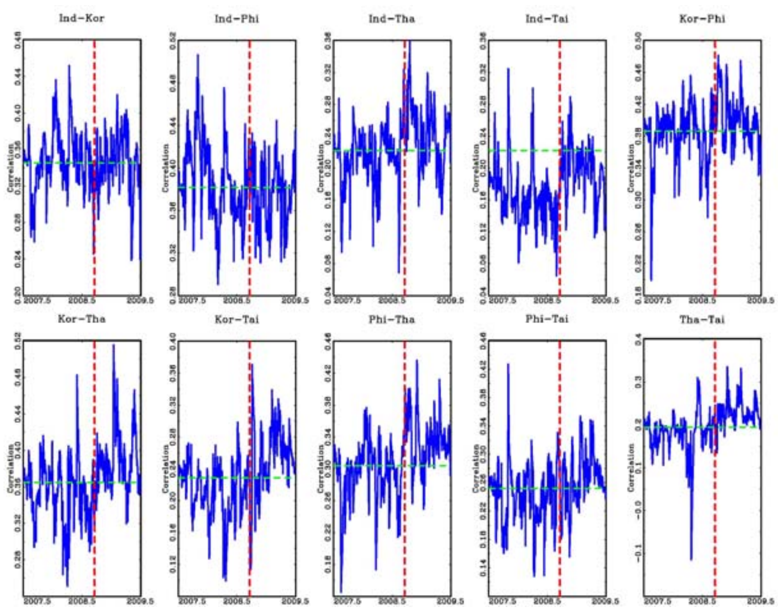
(b) Across Local Markets

Note: The solid line and the dotted horizontal line indicate the dynamic and the constant conditional correlation estimate, respectively. The dashed vertical line indicates the Lehman failure on September 15, 2008.

Figure 5. DCC and CCC Estimates: Foreign Exchange Rate Returns



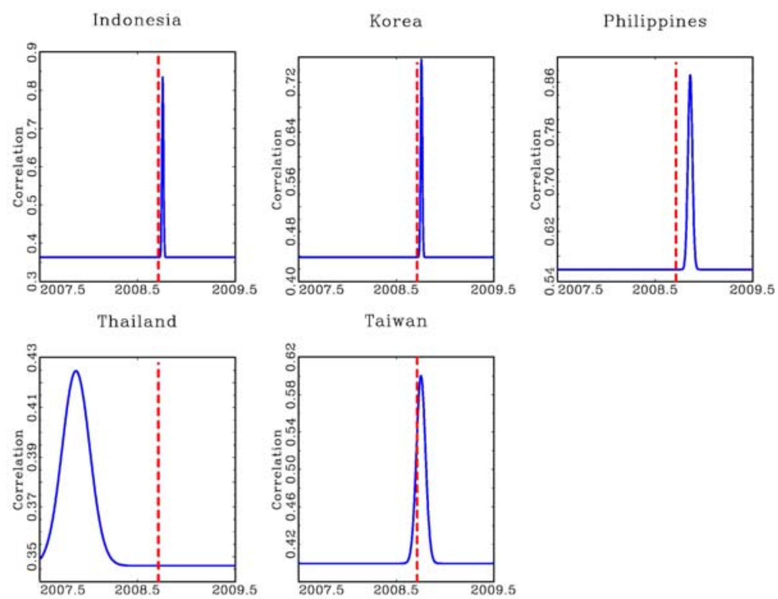
(a) With the Euro/US$



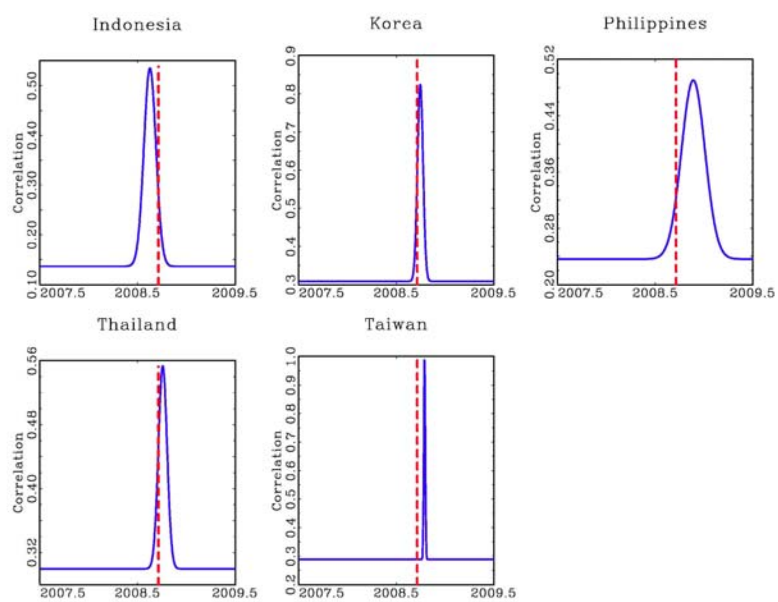
(b) Across Local Markets

Note: The solid line and the dotted horizontal line indicate the dynamic and the constant conditional correlation estimate, respectively. The dashed vertical line indicates the Lehman failure on September 15, 2008.

Figure 6. Nonlinear Conditional Correlation Estimates



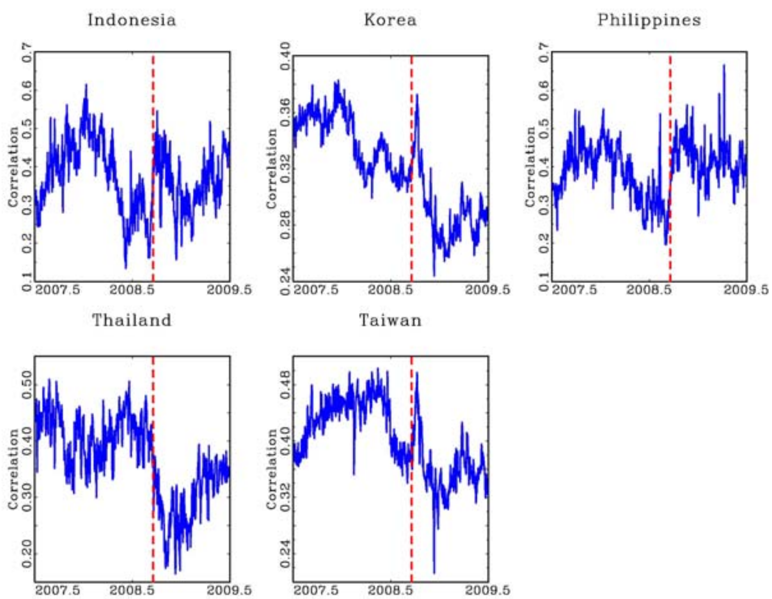
(a) Stock Price Returns



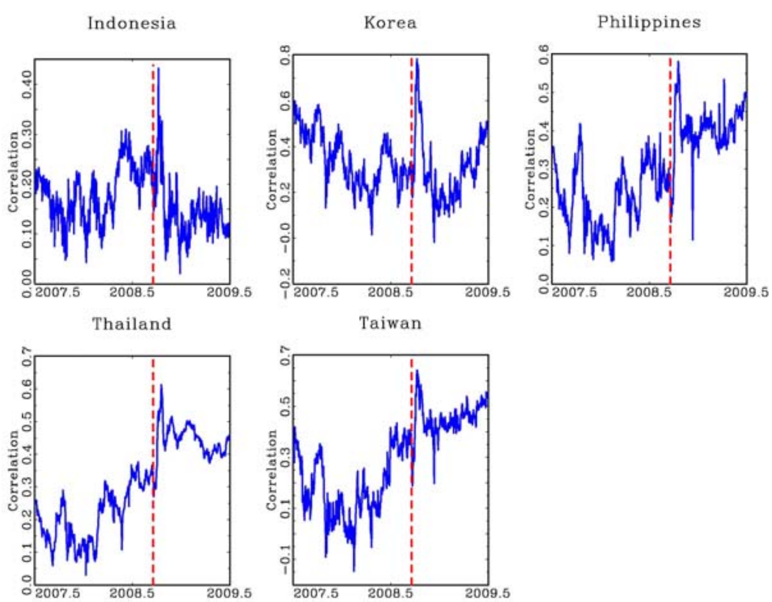
(b) Foreign Exchange Rate Returns

Note: The solid and the dotted lines indicate the ESTAR and the threshold conditional correlation estimates, respectively. The dashed vertical line indicates the Lehman failure on September 15, 2008.

Figure 7. DCCX Estimates by NLCC-MGARCH Models



(a) Stock Price Returns



(b) Foreign Exchange Rate Returns

Note: The dashed vertical line indicates the Lehman failure on September 15, 2008.