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# Spillover Effects of the U.S. Financial Crisis on Financial Markets in Emerging Asian Countries

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# Spillover Effects of the U.S. Financial Crisis on Financial Markets in Emerging Asian Countries

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### *Abstract*

We examine spillover effects of the recent U.S. financial crisis on five emerging Asian countries by estimating conditional correlations of financial asset returns across countries using multivariate GARCH models. We propose a novel approach that simultaneously estimates the conditional correlation coefficient and the effects of its determining factors over time, which can be used to identify the channels of spillovers. We find some evidence of financial contagion around the collapse of Lehman Brothers in September 2008. We further find a 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 be significant factors affecting 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 U.S. 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 U.S. until the summer of 2008. This relatively quiet 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 three months following September 15, 2008. During the same period, the Korean Won depreciated against the U.S. dollar by 19.2% as global risk aversion spurred demand for a safe asset (ironically, U.S. dollars), which led to strong deteriorating spillover effects on real sectors.

Although understanding the nature of contagion or spillover effect in financial markets is of fundamental importance, the 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 disappears when unconditional cross-market correlation coefficients are corrected for bias [see, among others, King and Wadhwani, 1990; Lee and Kim, 1993; Calvo and Reinhart, 1996]. 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 U.S. crisis to financial markets in five emerging Asian economies: Indonesia, Korea, the Philippines, Thailand, and Taiwan. We choose these emerging economies instead of countries with fully developed financial markets because financial markets in developed countries are well integrated with each other. So it seems rather obvious that adverse (or favorable) shocks would propagate to other target countries through highly integrated financial market channels as well as real activities channels. However, the propagation mechanisms in these emerging Asian countries are not currently very well identified because they are not fully integrated with the rest of the world including the U.S. and emerging markets generally show low correlations with developed markets.

Although China is one of the most influential economies among Asian countries, we exclude China in our analysis because our analysis heavily relies on marketable assets where government interventions play a limited role. For example, Chinese Yuan has virtually stayed pegged to the U.S. dollar for about two years since the summer of 2008. Their stock markets are not fully accessible to foreign traders yet. Other important variables such as interest rates also seem fairly closely influenced by the government. Since we are interested in the propagation mechanism derived from activities in private sectors, we decide not to include China in the present analysis, focusing on emerging Asian economies with relatively more market-oriented financial markets.

We are particularly interested in the following questions: 1) Is there empirical evidence of contagion from the U.S. to emerging Asian financial markets? 2) If so, when did it occur and for how long did it last? 3) More importantly, through what channels did the contagion spread to those markets? To address these questions, we employ an array of multivariate generalized autoregressive conditional heteroskedasticity (MGARCH) models.

To address the first two questions, we employ the conventional BEKK model by Engle and Kroner (1995) and Engle's (2002) dynamic conditional correlation (DCC) model in addition to our own MGARCH model. Throughout the paper, we focus on time-varying dynamic conditional correlations during the recent crisis instead of unconditional correlation coefficients because in our view the latter lacks practical usefulness from policy perspectives. Overall, transitions from the tranquil period to the turmoil period seemed to occur very quickly and lasted for fairly short period of time. This implies that these countries experienced 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 target countries tends to increase rapidly during the crisis.

To address 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 to estimate both the dynamic conditional correlation and the effects of explanatory variables simultaneously in a unified framework. The DCCX-MGARCH method can be quite useful in investigating economic fundamental variables that 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 the time-varying conditional correlations. We consider the following three channels of contagion. The first one is the factors that proxy the vulnerability of the U.S. financial markets. For this purpose, we consider the VIX index, the Chicago Board Options Exchange market volatility index, which is a popular measure of the implied volatility of S&P 500 index options. The TED spread, the difference between the three-month LIBOR and the three-month T-bill interest rate, and the daily 3-month U.S. dollar Libor-overnight index swap (OIS) spread are also considered as liquidity availability measures. Second, 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.

We find 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 paper is organized as follows. Section 2 provides a brief literature review. In Section 3, we present our empirical models and discuss estimation techniques we employ. Section 4 describes the data and presents the empirical results. Some concluding remarks and policy implications are provided in Section 5.

## 2. Literature review

The empirical literature on spillover or 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) through what channels adverse shocks propagate to other countries (markets) from the source country (market).

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 periods. If the correlation coefficient increases significantly during the crisis, this may imply a statistically higher degree of 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 investigate.[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 for the bias, Forbes and Rigobon report virtually no evidence of contagion during crises in the past, including the 1997 Asian crisis, the 1994 Mexican Peso (devaluation) crisis, and the 1987 U.S. 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 U.S. stock market crash. Edwards (1998) finds similar evidence in international bond 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 (i.e., contagion) after the 1994 Peso crisis, while finding some evidence of contagion after the 1997 Asian crisis. It should be noted, however, that these analyses do not provide direct evidence

[1] King and Wadhwani (1990) investigate stock return correlations between the U.S., the U.K., and Japan and report a significant increase in the cross-country correlation coefficients of stock returns after the 1987 U.S. 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.

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

against Forbes and Rigobon (2002) because Forbes and Rigobon focus on permanent changes in unconditional moments rather than conditional ones.

Another group of researchers employ the dynamic conditional correlation (DCC) MGARCH model developed 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, they do not make an arbitrary assumption on the timing of turmoil periods, since it does not rely on sub-sample analyses. Examples include, among others, Chiang et al. (2007), Frank and Hesse (2009), and Hwang et al. (2010). We employ this approach in this paper.

The second issue, which can be more important than the first one from policy perspectives, has drawn relatively little 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 exposure) that may have allowed the recent U.S. crisis to spread to other countries. They find little evidence that these channels are closely related to the incidence of the crisis.[4] However, the contagion due to financial channels seems highly plausible 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 in exacerbating contagious effects is to compare dynamic conditional correlations across countries and across relevant economic variables (e.g., Frank and Hesse, 2009). Our DCCX-MGARCH model is different from such models in that our model 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, new aspect of our model. Since it provides information on what

[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.

variables play dominant roles in channeling 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 BEKK Model

We first employ the conventional BEKK model (Engle and Kroner, 1995) as a benchmark to estimate time-varying conditional correlations of international asset returns.

Let $\boldsymbol{y}_t = \left[y_{1,t}\ y_{2,t}\ \ldots\ y_{k,t}\right]'$ be a $k$ by 1 vector of asset returns that obeys the following stochastic vector autoregressive (VAR) process:

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

where $\boldsymbol{\Gamma}(L)$ is the lag polynomial matrix. The conditional distribution of filtered asset returns, a vector of residuals, is assumed to be normal,

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

where $\Omega_{t-1}$ is the adaptive information set at time $t-1$.[5]

We utilize the conventional BEKK model with multivariate GARCH(1,1) specification, whose conditional covariance matrix $\boldsymbol{H}_t$ is given by:

$$\boldsymbol{H_t} = \boldsymbol{M'M} + \boldsymbol{A'e_{t-1}e'_{t-1}A} + \boldsymbol{B'H_{t-1}B}. \tag{3}$$

Especially for a bivariate system,

[5] Note that the conditional expectation of $\mathbb{E}_t\boldsymbol{y}_{t+j}$ is a function of $\boldsymbol{\Gamma}(L)$. Therefore, one can interpret the residual vector $\boldsymbol{e}_t$ as unexpected changes in asset returns.

$$\boldsymbol{M} = \begin{bmatrix} \omega_{11} & \omega_{12} \\ 0 & \omega_{22} \end{bmatrix}, \boldsymbol{A} = \begin{bmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{bmatrix}, \boldsymbol{B} = \begin{bmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{bmatrix}.$$

Specifically,

$$h_{11,t} = \alpha_{11}^2 e_{1,t-1}^2 + \alpha_{21}^2 e_{2,t-1}^2 + \beta_{11}^2 h_{11,t-1} + \beta_{21}^2 h_{22,t-1} + \mathrm{X}_1,$$

$$h_{22,t} = \alpha_{12}^2 e_{1,t-1}^2 + \alpha_{22}^2 e_{2,t-1}^2 + \beta_{12}^2 h_{11,t-1} + \beta_{22}^2 h_{22,t-1} + \mathrm{X}_2,$$

where $h_{ij,t}$ denotes the $(i,j)^{\text{th}}$ component of $\boldsymbol{H_t}$, that is, the conditional variance or covariance, $e_{i,t}$ is the $i^{\text{th}}$ component of $\boldsymbol{e_t}$, and $\mathrm{X}_i$ is the remaining terms that include cross products. Note that off-diagonal elements of $\boldsymbol{A}$ and $\boldsymbol{B}$ provide information on “news effect” and “volatility spillover effect”, respectively, while diagonal elements deliver its own ARCH and GARCH effects. For example, significant estimate for $\beta_{21}$ implies a statistically significant volatility spillover from asset return 2 to asset return 1.[6]

Conditional correlation is measured as usual by the following:

$$\rho_{i,j,t} = \frac{h_{i,j,t}}{\sqrt{h_{i,i,t} h_{j,j,t}}}. \tag{4}$$

### 3.2 The Dynamic Conditional Correlation Model

We next employ the dynamic conditional correlation (DCC) estimator (Engle, 2002). The DCC-MGARCH model can be viewed as a generalization of the constant conditional correlation (CCC) estimator (Bollerslev, 1990).

The conditional covariance matrix $\boldsymbol{H}_t$ is now defined as,

$$\boldsymbol{H}_t = \boldsymbol{D}_t \boldsymbol{R}_t \boldsymbol{D}_t, \tag{5}$$

[6] Note also the sign of these parameter estimates does not matter, because their squared values affect the conditional variances.

where $\boldsymbol{D}_t$ is the diagonal matrix with the conditional variances along the diagonal, that is, $\boldsymbol{D}_t = \sqrt{diag\{\boldsymbol{H}_t\}}$, and $\boldsymbol{R}_t$ is the time-varying correlation matrix.[7]

Equation (5) can be re-parameterized as follows with standardized returns, $\boldsymbol{\varepsilon}_t = \boldsymbol{D}_t^{-1}\boldsymbol{e}_t$:

$$\mathbb{E}_{t-1}\boldsymbol{\varepsilon}_t\boldsymbol{\varepsilon}_t' = \boldsymbol{D}_t^{-1}\boldsymbol{H}_t\boldsymbol{D}_t^{-1} = \boldsymbol{R}_t = [\rho_{i,j,t}]. \tag{6}$$

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

$$\rho_{i,j,t} = \frac{q_{i,j,t}}{\sqrt{q_{i,i,t}q_{j,j,t}}}, \tag{7}$$

where

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

and $\bar{\rho}_{i,j}$ is the unconditional correlation between $\varepsilon_{i,t}$ and $\varepsilon_{j,t}$. Non-negative scalars $\alpha$ and $\beta$ are assumed to satisfy the stationarity assumption, $\alpha + \beta < 1$.[8]

In matrix form,

$$\boldsymbol{Q}_t = \overline{\boldsymbol{Q}}(1-\alpha-\beta) + \alpha\boldsymbol{\varepsilon}_{t-1}\boldsymbol{\varepsilon}_{t-1}' + \beta\boldsymbol{Q}_{t-1}, \tag{8}$$

where $\overline{\boldsymbol{Q}}$ is the unconditional correlation matrix of $\boldsymbol{\varepsilon}_t$. $\boldsymbol{R}_t$ is then obtained by

$$\boldsymbol{R}_t = (\boldsymbol{Q}_t^*)^{-1/2}\boldsymbol{Q}_t(\boldsymbol{Q}_t^*)^{-1/2}, \tag{9}$$

where $\boldsymbol{Q}_t^* = diag\{\boldsymbol{Q}_t\}$.

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[7] Bollerslev's CCC model assumes $\boldsymbol{H}_t = \boldsymbol{D}_t\boldsymbol{R}\boldsymbol{D}_t$, where $\boldsymbol{R}$ is a $k$ by $k$ time-invariant (symmetric) correlation matrix.
[8] If $\alpha + \beta = 1$, that is, when $q_{i,j,t}$ is nonstationary, one may use the exponential smoothing estimator.

Engle proposes a two-step approach for estimating the DCC model. When $k = 2$, the log-likelihood function is,

$$\mathcal{L} = -\frac{1}{2}\sum_{t=1}^{T}\left(2\log(2\pi) + \log|\boldsymbol{H}_t| + \boldsymbol{e}_t'\boldsymbol{H}_t^{-1}\boldsymbol{e}_t\right)$$

$$= -\frac{1}{2}\sum_{t=1}^{T}\left(2\log(2\pi) + \log|\boldsymbol{D}_t\boldsymbol{R}_t\boldsymbol{D}_t| + \boldsymbol{e}_t'\boldsymbol{D}_t^{-1}\boldsymbol{R}_t^{-1}\boldsymbol{D}_t^{-1}\boldsymbol{e}_t\right)$$

$$= -\frac{1}{2}\sum_{t=1}^{T}\left(2\log(2\pi) + 2\log|\boldsymbol{D}_t| + \log|\boldsymbol{R}_t| + \boldsymbol{\varepsilon}_t'\boldsymbol{R}_t^{-1}\boldsymbol{\varepsilon}_t\right).$$

Adding and subtracting $\boldsymbol{e}_t'\boldsymbol{D}_t^{-1}\boldsymbol{D}_t^{-1}\boldsymbol{e}_t = \boldsymbol{\varepsilon}_t'\boldsymbol{\varepsilon}_t$ to it and rearranging it, we rewrite the log-likelihood as the sum of the volatility component ($\mathcal{L}_V$) and correlation component ($\mathcal{L}_C$). Let $\boldsymbol{\theta}$ denote a vector of parameters in $\boldsymbol{D}_t$ and $\boldsymbol{\phi}$ be other parameters in $\boldsymbol{R}_t$. Then,

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

where

$$\mathcal{L}_V(\boldsymbol{\phi}) = -\frac{1}{2}\sum_{t=1}^{T}\sum_{i=1}^{2}\left(\log(2\pi) + \log\left(h_{i,i,t}\right) + \frac{e_{i,t}^2}{h_{i,i,t}}\right)$$

$$\mathcal{L}_C(\boldsymbol{\phi}) = -\tfrac{1}{2}\textstyle\sum_{t=1}^{T}\left(\boldsymbol{\varepsilon}_t'\boldsymbol{R}_t^{-1}\boldsymbol{\varepsilon}_t - \boldsymbol{\varepsilon}_t'\boldsymbol{\varepsilon}_t + \log|\boldsymbol{R}_t|\right).$$

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

### 3.3 The DCCX-MGARCH Model

We now propose our novel DCC-MGARCH model where the conditional correlation coefficient is determined by exogenous variables: DCCX-MGARCH model.

We assume the following for $\boldsymbol{H}_t$ from (2) after filtering by the VAR fit in (1):

$$h_{i,i,t} = \omega_i + \alpha_i e_{i,t}^2 + \beta_i h_{i,i,t-1}^2, \tag{10}$$
$$h_{i,j,t} = \rho_{i,j}(\boldsymbol{x}_t)(h_{i,i,t} h_{j,j,t})^{1/2},$$

where $-1 < \rho_{i,j}(\boldsymbol{x}_t) < 1$ $(i, j = 1,2)$ is a monotonic increasing function of $\boldsymbol{x}_t$, a $q$ by 1 vector of economic fundamental variables that affect the size of the conditional correlation.

Note that this specification is similar to the one proposed by Berben and Jansen (2005), who proposed a time-dependent conditional correlation. That is, they allow regime changes in $\rho_{i,j}$ with a time transition variable. Our model in (10) is a state-dependent model with an assumption that regime changes depend on the current state of the economy, proxied by $\boldsymbol{x}_t$, rather than the time itself.[9] This approach is useful for identifying propagation channels of potential effects of crises.

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

$$\rho_{i,j}(\boldsymbol{x}_t) = 2\left[\frac{\exp\left(\boldsymbol{\theta}_{i,j}'\boldsymbol{x}_t\right)}{1+\exp\left(\boldsymbol{\theta}_{i,j}'\boldsymbol{x}_t\right)}\right] - 1, \tag{11}$$

where $\boldsymbol{\theta}_{i,j} = \left[\theta_{i,j,1}\ \ \theta_{i,j,2} \ldots\ \theta_{i,j,q}\right]'$ and $\boldsymbol{x}_t = \left[x_{1,t}\ \ x_{1,t}\ \ \ldots\ \ x_{q,t}\right]'$. Note that this parameterization allows $\rho_{i,j}(\boldsymbol{x}_t)$ to be bounded below and above by $-1$ and $1$, respectively, which provides a correct specification for the conditional correlation. Note that a significant estimate for $\theta_{i,j,q}$ implies a non-negligible effect of $x_{q,t}$ on the conditional correlation $\rho_{i,j}(\boldsymbol{x}_t)$.

[9] Alternatively, one may consider a model where $\boldsymbol{x}_t$ appears in the mean equation in (1) rather than the variance equation. We choose the current model because we are more interested in the effect of unexpected changes rather than the effect of predictable components.

## 4. Empirical Results

### 4.1 Data and Summary Statistics

We utilize daily observations of stock price 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 U.S. dollar. Asset returns are calculated by taking two-day differentials of logged asset prices, multiplied by 100. We study the dynamic conditional correlations between daily returns of the S&P 500 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 the U.S. dollar 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 (Figure 1). Similarly, sudden depreciations of most currencies against the U.S. dollar were observed during the Lehman failure with exceptions of the Philippines and Taiwan (Figure 2). It should also be noted that the GARCH volatility substantially rose around the Lehman failure for all equity returns and for three exchange rates, the Euro, the Indonesian Rupiah, 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 U.S. 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 U.S. dollar lost its value 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.[10] The fundamental variables that determine the size of DCC are briefly discussed below.

One motivation for 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 five 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 concern.[11] The TED spread is used as a measure of the level of financial stress in the interbank market. The TED

[10] Similarly, Eichengreen et al. (2009) use the VIX index, the TED spread, and the dollar 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.

[11] 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.

spread is the difference between the three-month LIBOR and the yield on the U.S. Treasury bills with the same maturity.[12]

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 increase reflecting banks' reluctance to extend longer maturity loans. The Libor-OIS spreads increased 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 the conventional BEKK-MGARCH (Engle and Kroner, 1995) estimation results in Tables 2 and 3 as a benchmark. We also implement the DCC-MGARCH model along with the CCC-MGARCH estimations (Tables 4 and 5) and compare the estimated dynamic conditional correlations with those from the BEKK-MGARCH model (See Figures 3, 4, and 5). The dashed vertical line in the graphs indicates September 15, 2008 when financial market instability culminated after the failure of Lehman Brothers.

As we can see in Tables 2 and 3, most of our BEKK model estimates are highly significant and imply that stock markets and foreign exchange markets are closely linked

[12] 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).

internationally. Specifically, overall significant estimates for diagonal components imply strong ARCH ($\alpha_{11}$, $\alpha_{22}$) and GARCH effects ($\beta_{11}$, $\beta_{22}$). Statistically significant estimates for off-diagonal components suggest non-negligible cross-market news effects ($\alpha_{12}$, $\alpha_{21}$) and volatility spillover effects ($\beta_{12}$, $\beta_{21}$). Overall, spillover effects from the U.S. (or Euro) to emerging Asian countries ($\beta_{12}$) are greater than the effects in opposite direction ($\beta_{21}$), which is not surprising.

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

One notable finding is that for the equity returns, the correlation coefficient estimates increased substantially around the Lehman failure with an exception of Thailand. However, unusually high correlations were short-lived as they quickly moved back to the previous lower levels around October 2008. Similar movements around the Lehman failure are observed for the exchange rate changes. Sudden rises in the correlation of exchange rates are more pronounced than those in the case of stock prices. We also observe similar spikes across local markets.[13] In sum, our results imply that the U.S. financial crisis had a strong spillover effect on financial asset

[13] 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.

returns in most emerging Asian countries when the news of Lehman Brothers failure was revealed in September 2008.

--- Tables 2, 3, 4, 5 about here ---

--- Figures 3, 4, 5 about here ---

Next, we turn to an analysis of factors affecting the conditional correlation coefficient using the DCCX-MGARCH model. A number of variables can be considered for the factors that play important roles in affecting the dynamic conditional correlation.

We first choose the factors that are related to the financial conditions of the source country where the crisis originates. We consider the VIX index as a measure of the U.S. financial market stability, and the TED spread and the dollar Libor-OIS spread as measures of the U.S. risk premium or liquidity availability. We expect these financial instability or 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. Third, we also consider the amount of foreign buy- and sell-order flows as an exogenous factor in local stock markets. A 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 6 and 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 in all countries. The sovereign CDS premium has a significant effect on the correlations in Indonesia and Philippines, but with a negative sign. For those two countries, the VIX index has a significantly positive effect, implying that uncertainty in the U.S. stock market may have spread to those countries.

Based on these estimates, we find that the spillover effect of the U.S. stock market shocks is mainly due to sudden increases in foreign capital and propagations of U.S. 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 in the safest and most liquid assets such as developed 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 U.S. stock returns and returns in 83 countries, they also find that a larger share of U.S. investors' asset holdings in foreign markets is associated with a more pronounced reaction to the U.S. crisis.[14]

Second, the Libor-OIS spread, the sovereign CDS premium, and foreign capital appear to have overall positive effects on the conditional correlations in international foreign exchange markets with an exception of Korea for the CDS premium. Especially, the amount of foreign buy- and sell-trades has a significantly positive effect on two out of five 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

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

play important roles in affecting the conditional correlations in international foreign exchange markets.[15]

The results on exchange rates seem consistent with arguments that the current global crisis spreads quickly to other countries, first through the lack of available liquidity and then through concerns about 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 U.S. by U.S. investors, a flight-to-safety phenomenon by U.S. and non-U.S. investors, an increased need for U.S. dollar liquidity and an unwinding of carry trade positions may all have played a role in the sharp appreciation trend of the U.S. dollar.

--- Tables 6, 7 about here ---

--- Figure 6 about here ---

## 5. Concluding Remarks

In this paper, we use an array of MGARCH models to estimate dynamic conditional correlations of financial asset returns between the U.S. and five emerging Asian countries. Our major findings imply that the recent U.S. financial crisis, triggered by the collapse of Lehman Brothers in September 2008, has a non-negligible but short-lived spillover effect on emerging Asian countries. Our analysis shows that the conditional correlation increased rapidly to a much higher level around the Lehman Brothers failure period and such a high correlation has persisted for a

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

fairly short period of time. Put differently, we find a short-lived but non-negligible financial contagion from the U.S. to emerging Asian countries.

We also investigate major factors that influence the size of conditional correlations using a novel DCCX-MGARCH model. Especially, we find a substantial role of 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 the dynamic conditional correlations.

Our analysis provides some policy implications. Our estimated conditional correlations imply that the spillover from the U.S. financial crisis may have occurred abruptly. While financial contagion seems to persist for a fairly short period of time, its impact 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 deteriorations in both the capital and the foreign exchange markets. This possibility calls for a need to construct a financial stabilization mechanism against contagions 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 have 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 |
| Max | 0.10246 | 0.07623 | 0.11284 | 0.07056 | 0.08054 | 0.07549 |
| Min | -0.09470 | -0.10954 | -0.11172 | -0.13089 | -0.06735 | -0.1109 |
| 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 | 8.043 |

| | *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 |
| Max | 0.06261 | 0.05356 | 0.10693 | 0.01703 | 0.01648 | 0.01237 |
| Min | -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 |

Note: We use daily observations of stock indices and foreign exchange rates obtained from Bloomberg for the period from April 2, 2007 to August 31, 2009. Exchange rates are national currency prices of the U.S. dollar. Asset returns are calculated by taking two-day differentials of natural logarithm asset prices, multiplied by 100.

**Table 2. BEKK-MGARCH Model: Stock Price Returns**

$$\boldsymbol{e_t} = [e_{1,t} \quad e_{2,t}]', \boldsymbol{H_t} = \boldsymbol{M'M} + \boldsymbol{A'e_{t-1}e'_{t-1}A} + \boldsymbol{B'H_{t-1}B}$$

$$\boldsymbol{M} = \begin{bmatrix} \omega_{11} & \omega_{12} \\ 0 & \omega_{22} \end{bmatrix}, \boldsymbol{A} = \begin{bmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{bmatrix}, \boldsymbol{B} = \begin{bmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{bmatrix}$$

| | IN | KR | PH | TH | TW |
|---|---|---|---|---|---|
| $\omega_{11}$ | 0.3819* | 0.2659* | 0.0198 | 0.2211* | -0.0025* |
| | (0.000) | (0.000) | (0.243) | (0.000) | (0.000) |
| $\omega_{12}$ | 0.0000 | -0.0011 | 0.0672 | 0.0002 | 0.3035* |
| | (0.655) | (0.067) | (0.393) | (0.701) | (0.000) |
| $\omega_{22}$ | -0.2610* | -0.0769* | 0.1422* | 1.3682* | 0.0659* |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| $\alpha_{11}$ | 0.3029* | 0.0282 | 0.1368* | 0.2153* | 0.1919* |
| | (0.000) | (0.426) | (0.000) | (0.000) | (0.000) |
| $\alpha_{12}$ | -0.1628* | -0.3710* | 0.3700* | 0.1338* | -0.4293* |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| $\alpha_{21}$ | 0.1231* | -0.2988* | -0.1749* | -0.3125* | 0.1390* |
| | (0.000) | (0.006) | (0.000) | (0.000) | (0.000) |
| $\alpha_{22}$ | 0.2926* | 0.2185* | 0.5083* | 0.0015 | 0.3161* |
| | (0.000) | (0.000) | (0.000) | (0.758) | (0.000) |
| $\beta_{11}$ | 0.8958* | 0.8170* | 0.9772* | 1.0266* | 0.8621* |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| $\beta_{12}$ | 0.1332* | 0.1896* | -0.1039* | -0.2902* | 0.2217* |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| $\beta_{21}$ | -0.0646* | -0.1072* | 0.0395* | 0.4985* | -0.0555* |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| $\beta_{22}$ | 0.9516* | 1.0081* | 0.8913* | -0.6697* | 0.9349* |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| $-lnL$ | 1007.4 | 996.3 | 944.5 | 999.5 | 975.6 |

Note: Subscript 1 and 2 denote the U.S. and each of national countries. $e_t$ is a 2 by 1 vector of residuals filtered by a VAR(1) process for stock returns in countries 1 and 2.

**Table 3. BEKK-MGARCH Model: Exchange Rate Returns**

$$\boldsymbol{e_t} = [e_{1,t} \quad e_{2,t}]', \boldsymbol{H_t} = \boldsymbol{M'M} + \boldsymbol{A'e_{t-1}e'_{t-1}A} + \boldsymbol{B'H_{t-1}B}$$

$$\boldsymbol{M} = \begin{bmatrix} \omega_{11} & \omega_{12} \\ 0 & \omega_{22} \end{bmatrix}, \boldsymbol{A} = \begin{bmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{bmatrix}, \boldsymbol{B} = \begin{bmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{bmatrix}$$

| | IN | KR | PH | TH | TW |
|---|---|---|---|---|---|
| $\omega_{11}$ | 0.2972* | 0.0520* | 0.1876* | 0.0779* | 0.0688* |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| $\omega_{12}$ | -0.0001 | 0.0001 | 0.0000 | 0.0251* | 0.1348* |
| | (0.661) | (0.998) | (0.982) | (0.000) | (0.000) |
| $\omega_{22}$ | 0.1257* | -0.2714* | -0.3410* | -0.2911* | -0.0665 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.105) |
| $\alpha_{11}$ | -0.2327* | 0.2413* | 0.1760* | 0.3269* | 0.2199* |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| $\alpha_{12}$ | -0.4204* | 0.0742* | 0.1849* | 0.3435* | 0.3383* |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| $\alpha_{21}$ | 0.0143 | -0.0107* | -0.0881* | -0.1865* | -0.0103* |
| | (0.1542) | (0.000) | (0.000) | (0.000) | (0.000) |
| $\alpha_{22}$ | 0.2882* | 0.8811* | 0.3900* | 0.5724* | 0.5439* |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| $\beta_{11}$ | 0.7338* | 0.9840* | 0.8988* | 0.9550* | 0.9441* |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| $\beta_{12}$ | 0.3071* | -0.0670* | 0.2180* | -0.2411 | 0.1075* |
| | (0.000) | (0.000) | (0.000) | (0.176) | (0.002) |
| $\beta_{21}$ | -0.1861* | 0.1535* | 0.1034* | 0.1920* | 0.0095* |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| $\beta_{22}$ | 0.9649* | 0.6791* | 0.6279* | 0.0462* | 0.7117* |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| $-lnL$ | 599.9 | 733.8 | 507.8 | 417.4 | 360.6 |

Note: Subscript 1 and 2 denote the Euro and each of national countries. $e_t$ is a 2 by 1 vector of residuals filtered by a VAR(1) process for exchange rate returns in countries 1 and 2.

## Table 4. CCC and DCC Model Estimates: Stock Price Returns

$$GARCH\text{: } h_{i,t} = \omega_i + \alpha_i e_{i,t}^2 + \beta_i h_{i,t-1}^2$$
$$CCC\text{: } \boldsymbol{H}_t = \boldsymbol{D}_t \boldsymbol{R} \boldsymbol{D}_t,\ \boldsymbol{D}_t = \sqrt{diag\{\boldsymbol{H}_t\}},\ \boldsymbol{R} = [\rho_{i,j}]$$
$$DCC\text{: } \boldsymbol{Q}_t = \overline{\boldsymbol{Q}}(1-\alpha-\beta) + \alpha \boldsymbol{\varepsilon}_{t-1}\boldsymbol{\varepsilon}_{t-1}' + \beta \boldsymbol{Q}_{t-1}$$

| | | US | IN | KR | PH | TH | TW |
|---|---|---|---|---|---|---|---|
| GARCH | $\omega_i$ | 0.0689* | 0.1807* | 0.1263* | 0.2112* | 0.0869* | 0.1144* |
| | | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| | $\alpha_i$ | 0.1312* | 0.1767* | 0.1162* | 0.1196* | 0.1265* | 0.1835* |
| | | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| | $\beta_i$ | 0.8502* | 0.7885* | 0.8516* | 0.8065* | 0.8601* | 0.7916* |
| | | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| CCC | $\rho_{1,j}$ | - | 0.3747* | 0.4174* | 0.5116* | 0.3715* | 0.3424* |
| | | | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| | $\rho_{2,j}$ | - | - | 0.5816* | 0.4418* | 0.5038* | 0.5853* |
| | | | | (0.000) | (0.000) | (0.000) | (0.000) |
| | $\rho_{3,j}$ | - | - | - | 0.4480* | 0.7069* | 0.5441* |
| | | | | | (0.000) | (0.000) | (0.000) |
| | $\rho_{4,j}$ | - | - | - | - | 0.4631* | 0.4285* |
| | | | | | | (0.000) | (0.000) |
| | $\rho_{5,j}$ | - | - | - | - | - | 0.4671* |
| | | | | | | | (0.000) |
| | $-ln\mathcal{L}$ | 6027.0 | | | | | |
| DCC | $\alpha$ | 0.0298* | | | | | |
| | | (0.000) | | | | | |
| | $\beta$ | 0.7844* | | | | | |
| | | (0.000) | | | | | |
| | $-ln\mathcal{L}$ | 6015.3 | | | | | |

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

## Table 5. CCC and DCC Model Estimates: Exchange Rate Returns

$$GARCH\text{: } h_{i,t} = \omega_i + \alpha_i e_{i,t}^2 + \beta_i h_{i,t-1}^2$$
$$CCC\text{: } \boldsymbol{H}_t = \boldsymbol{D}_t \boldsymbol{R} \boldsymbol{D}_t,\ \boldsymbol{D}_t = \sqrt{diag\{\boldsymbol{H}_t\}},\ \boldsymbol{R} = [\rho_{i,j}]$$
$$DCC\text{: } \boldsymbol{Q}_t = \overline{\boldsymbol{Q}}(1-\alpha-\beta) + \alpha \boldsymbol{\varepsilon}_{t-1}\boldsymbol{\varepsilon}'_{t-1} + \beta \boldsymbol{Q}_{t-1}$$

| | | Euro | IN | KR | PH | TH | TW |
|---|---|---|---|---|---|---|---|
| GARCH | $\omega_i$ | 0.0024* | 0.0103* | 0.0121* | 0.0072* | 0.0007* | 0.0009* |
| | | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| | $\alpha_i$ | 0.0651* | 0.1704* | 0.2737* | 0.0399* | 0.0846* | 0.1714* |
| | | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| | $\beta_i$ | 0.9349* | 0.8296* | 0.7263* | 0.9338* | 0.9150* | 0.8286* |
| | | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| CCC | $\rho_{1,j}$ | - | 0.1674* | 0.3023* | 0.2842* | 0.2968* | 0.3144* |
| | | | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| | $\rho_{2,j}$ | - | - | 0.3452* | 0.3816* | 0.2219* | 0.1771* |
| | | | | (0.000) | (0.000) | (0.000) | (0.000) |
| | $\rho_{3,j}$ | - | - | - | 0.3865* | 0.3649* | 0.2286* |
| | | | | | (0.000) | (0.000) | (0.000) |
| | $\rho_{4,j}$ | - | - | - | - | 0.3038* | 0.2520* |
| | | | | | | (0.000) | (0.000) |
| | $\rho_{5,j}$ | - | - | - | - | - | 0.1947* |
| | | | | | | | (0.000) |
| | $-ln\mathcal{L}$ | 2123.1 | | | | | |
| DCC | $\alpha$ | 0.0217* | | | | | |
| | | (0.000) | | | | | |
| | $\beta$ | 0.8543* | | | | | |
| | | (0.000) | | | | | |
| | $-ln\mathcal{L}$ | 2113.7 | | | | | |

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

## Table 6. DCCX-MGARCH Model Estimates: Stock Price Returns

$$h_{i,i,t} = \omega_i + \alpha_i e_{i,t}^2 + \beta_i h_{i,i,t-1}^2$$
$$h_{i,j,t} = \rho_{i,j}(\boldsymbol{x}_t)(h_{i,i,t} h_{j,j,t})^{1/2}$$
$$\rho_{i,j}(\boldsymbol{x}_t) = 2\left[\frac{\exp\left(\boldsymbol{\theta}'_{i,j}\boldsymbol{x}_t\right)}{1+\exp\left(\boldsymbol{\theta}'_{i,j}\boldsymbol{x}_t\right)}\right] - 1$$

***Variance Equation***

| | IN | KR | PH | TH | TW |
|---|---|---|---|---|---|
| $\omega_1$ | 0.0392* | 0.0445* | 0.0346* | 0.0439* | 0.0357 |
| | (0.032) | (0.018) | (0.045) | (0.025) | (0.060) |
| $\omega_2$ | 0.1943* | 0.0931* | 0.3518* | 0.0805* | 0.0648* |
| | (0.004) | (0.019) | (0.001) | (0.025) | (0.045) |
| $\alpha_1$ | 0.1247* | 0.1039* | 0.1010* | 0.1016* | 0.1057* |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| $\alpha_2$ | 0.1857* | 0.0903* | 0.1601* | 0.1410* | 0.0966* |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| $\beta_1$ | 0.8682* | 0.8835* | 0.8902* | 0.8861* | 0.8864* |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| $\beta_2$ | 0.7787* | 0.8853* | 0.7233* | 0.8390* | 0.8914* |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |

***Correlation Coefficient Equation***

| | IN | KR | PH | TH | TW |
|---|---|---|---|---|---|
| $\theta_{1,j,1}$ | 0.1055* | 0.1299* | 0.1815* | 0.1875* | 0.1671* |
| | (0.045) | (0.000) | (0.003) | (0.008) | (0.023) |
| $\theta_{1,j,2}$ | -0.8744* | -0.1357 | -0.4560* | 0.1316 | -0.0871 |
| | (0.014) | (0.281) | (0.014) | (0.708) | (0.405) |
| $\theta_{1,j,3}$ | 1.2683* | -0.1086 | 0.7900* | -0.4824 | -0.0296 |
| | (0.027) | (0.361) | (0.006) | (0.388) | (0.889) |
| $\theta_{1,j,4}$ | -0.0331 | 0.0646 | -0.0583 | 0.0790 | 0.1466 |
| | (0.799) | (0.502) | (0.559) | (0.694) | (0.370) |
| $-ln\mathcal{L}$ | 2201.4 | 2168.1 | 2078.9 | 2105.9 | 2192.7 |

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

**Table 7. DCCX-MGARCH Model Estimates: Exchange Rate Returns**

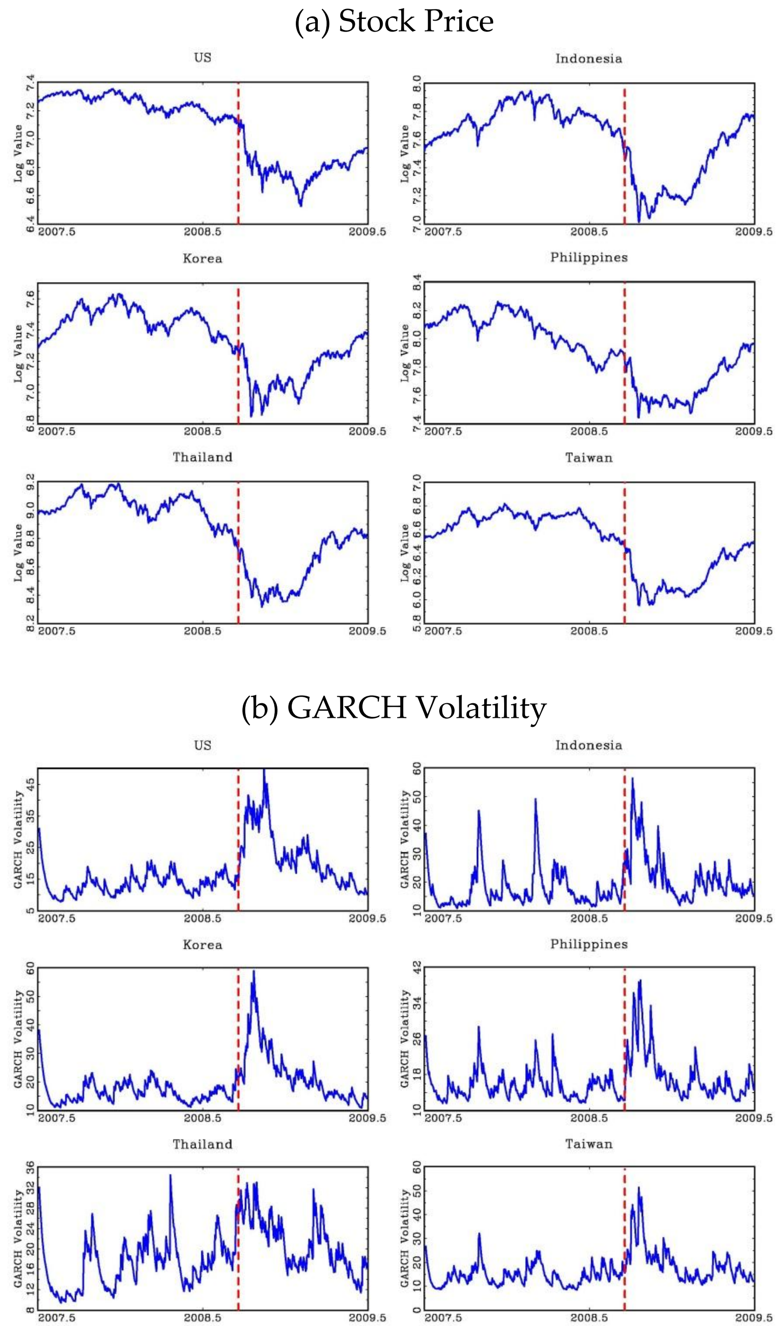
$$h_{i,i,t} = \omega_i + \alpha_i e_{i,t}^2 + \beta_i h_{i,i,t-1}^2$$
$$h_{i,j,t} = \rho_{i,j}(\boldsymbol{x}_t)(h_{i,i,t} h_{j,j,t})^{1/2}$$
$$\rho_{i,j}(\boldsymbol{x}_t) = 2\left[\frac{\exp(\boldsymbol{\theta}_{i,j}' \boldsymbol{x}_t)}{1+\exp(\boldsymbol{\theta}_{i,j}' \boldsymbol{x}_t)}\right] - 1$$

| | ***Variance Equation*** | | | | |
|---|---|---|---|---|---|
| | IN | KR | PH | TH | TW |
| $\omega_1$ | 0.0020 | 0.0027 | 0.0013 | 0.0018 | 0.0019 |
| | (0.256) | (0.132) | (0.382) | (0.296) | (0.273) |
| $\omega_2$ | 0.0079* | 0.0078* | 0.0113 | 0.0014* | 0.0008 |
| | (0.015) | (0.018) | (0.232) | (0.031) | (0.068) |
| $\alpha_1$ | 0.0805* | 0.0657* | 0.0684* | 0.0764* | 0.0739* |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| $\alpha_2$ | 0.2843* | 0.2474* | 0.0494* | 0.3064* | 0.0986* |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| $\beta_1$ | 0.9249* | 0.9356* | 0.9375* | 0.9291* | 0.9310* |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| $\beta_2$ | 0.7654* | 0.7195* | 0.9093* | 0.6959* | 0.9019* |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |

| | ***Correlation Coefficients Equation*** | | | | |
|---|---|---|---|---|---|
| | IN | KR | PH | TH | TW |
| $\theta_{i,j,1}$ | 0.0584 | 0.3180* | 0.0950 | 0.0392 | 0.2624* |
| | (0.231) | (0.000) | (0.533) | (0.794) | (0.039) |
| $\theta_{1,j,2}$ | 0.2915 | -0.2913* | 0.4338* | 0.3725* | 0.2729* |
| | (0.292) | (0.010) | (0.002) | (0.010) | (0.003) |
| $\theta_{1,j,3}$ | -0.7009 | -0.7527* | -0.5273* | -0.3638 | -0.6347* |
| | (0.350) | (0.002) | (0.015) | (0.208) | (0.004) |
| $\theta_{1,j,4}$ | 0.2338* | 1.0111* | 0.3834* | 0.3057 | 0.5569* |
| | (0.039) | (0.000) | (0.034) | (0.470) | (0.038) |
| $-ln\mathcal{L}$ | 1192.3 | 1231.8 | 1015.5 | 522.9 | 671.6 |

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

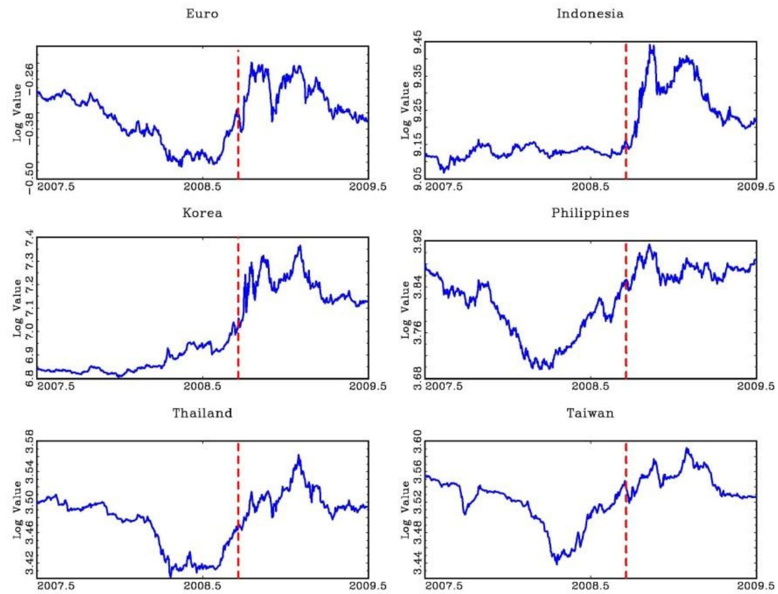
**Figure 1. Stock Price Data and GARCH Volatility Estimates**



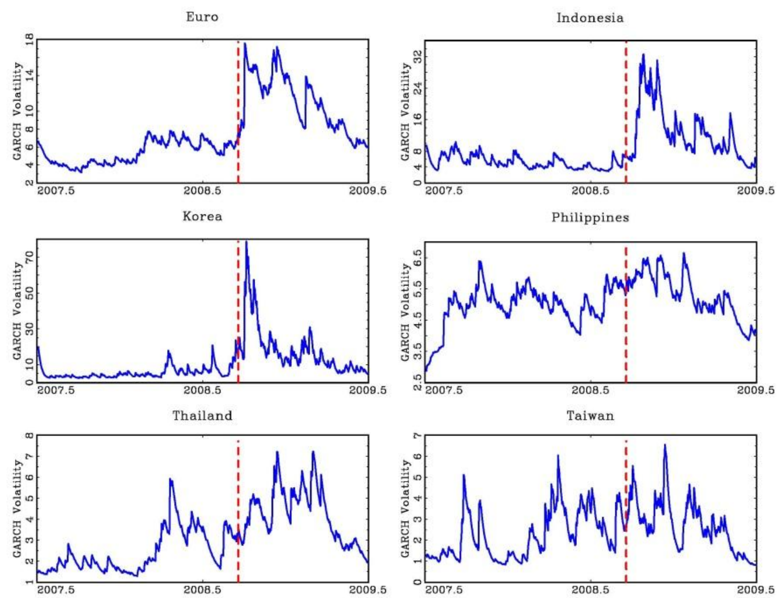

Note: The dashed vertical line indicates the Lehman failure on September 15, 2008.

**Figure 2. Exchange Rate Data and GARCH Volatility Estimates**

(a) Exchange Rate



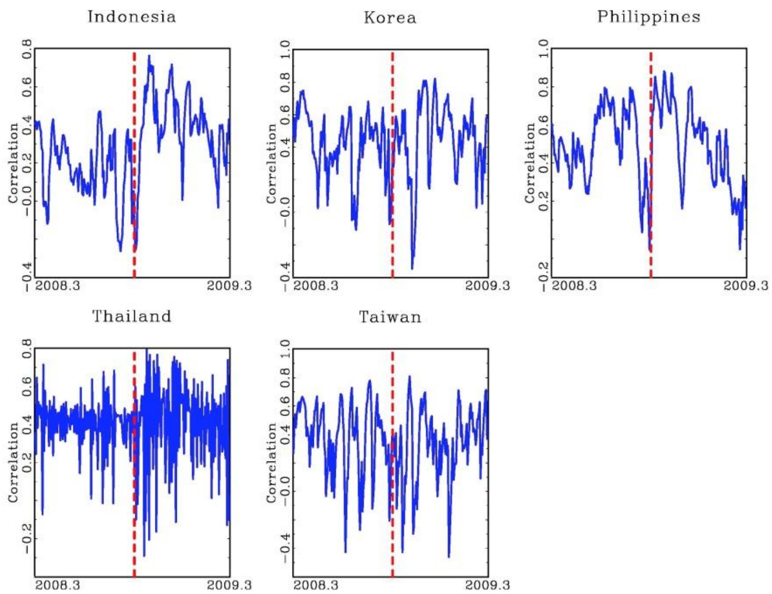

(b) GARCH Volatility



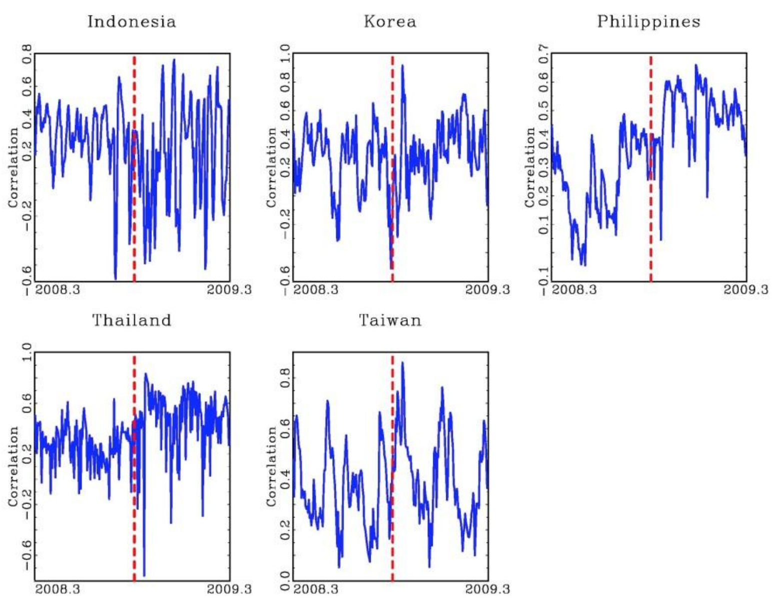

Note: The dashed vertical line indicates the Lehman failure on September 15, 2008.

## Figure 3. BEKK Conditional Correlation Estimates

(a) Stock Price Return



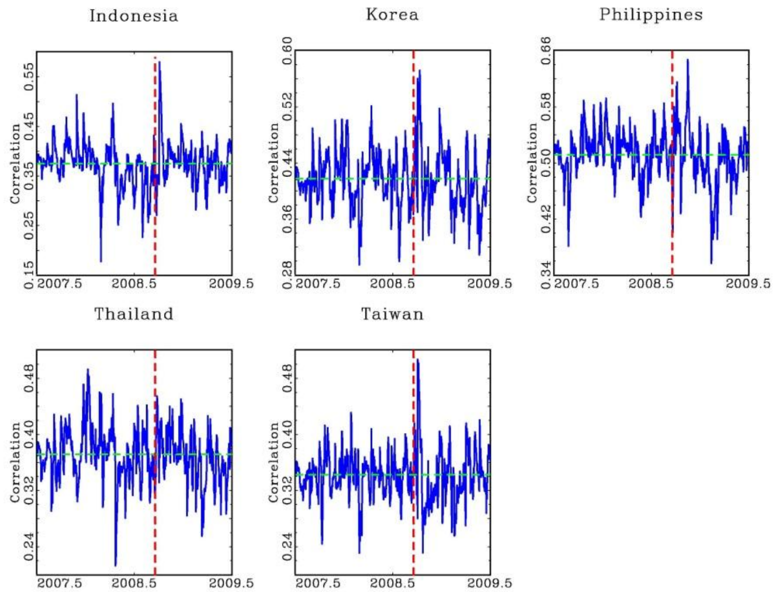

(b) Exchange Rate Return



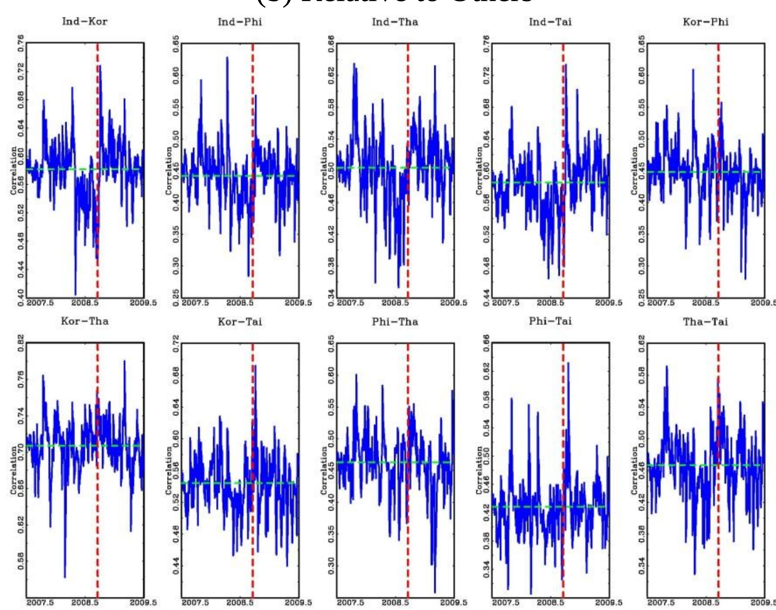

Note: The dashed vertical line indicates the Lehman failure on September 15, 2008.

**Figure 4. CCC and DCC Estimates: Stock Price Return**

(a) Relative to the US



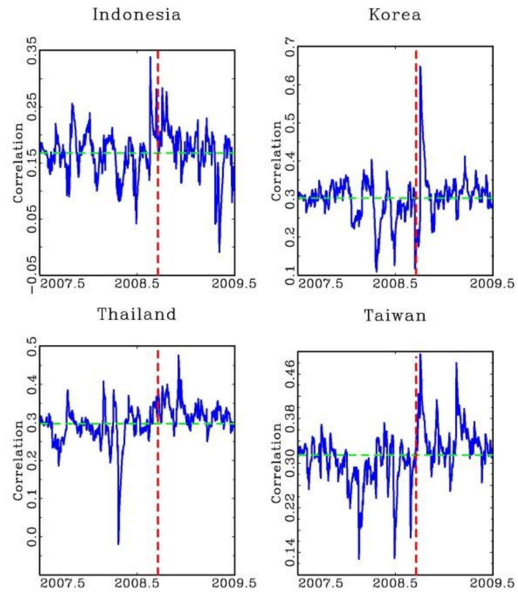

(b) Relative to Others



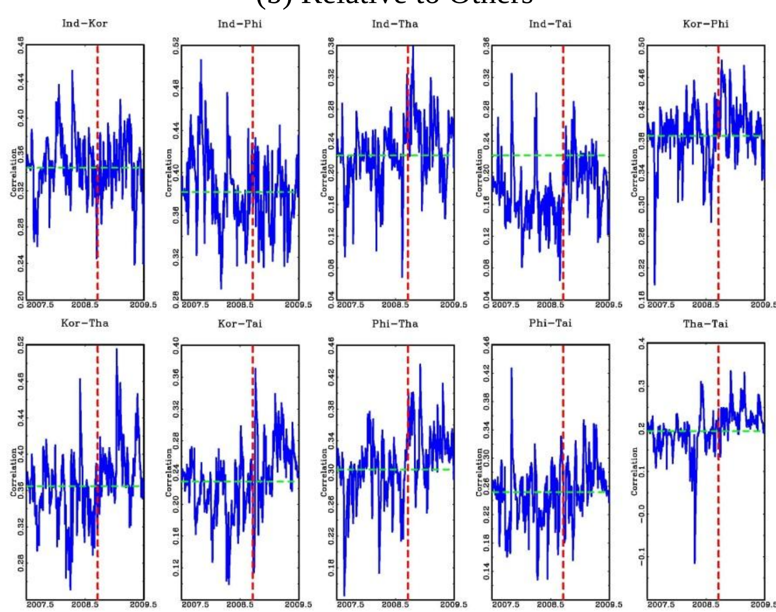

Note: The solid line and the dotted horizontal line indicate the dynamic and the constant conditional correlation estimate, respectively. The dashed vertical line indicates the Lehman failure on September 15, 2008.

## Figure 5. CCC and DCC Estimates: Exchange Rate Return

(a) Relative to the US



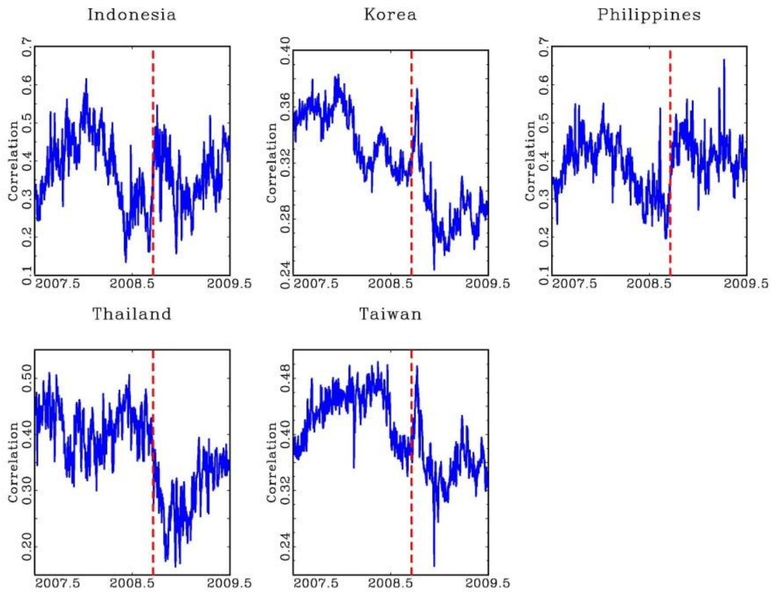

(b) Relative to Others



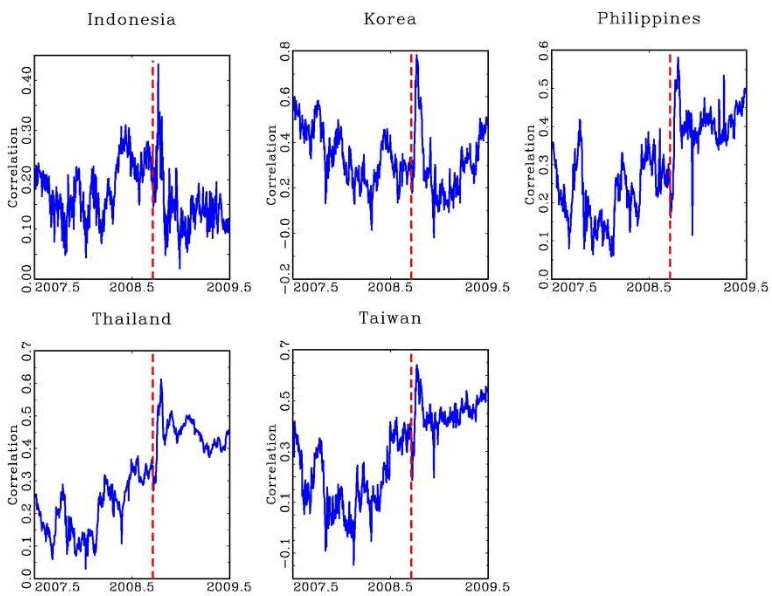

Note: The solid line and the dotted horizontal line indicate the dynamic and the constant conditional correlation estimate, respectively. The dashed vertical line indicates the Lehman failure on September 15, 2008.

**Figure 6. DCCX-MGARCH Estimates**

(a) Stock Price Return




(b) Exchange Rate Return




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