An Asymmetric Block Dynamic Conditional Correlation Multivariate GARCH Model

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Abstract

A new dynamic conditional correlation model is proposed in this paper. The Block DCC model for determining dynamic correlations between groups of financial assets is extended to account for the asymmetric effect between groups. Simulation results confirm the consistency of the maximum likelihood estimator of the Asymmetric Block DCC. Further simulations show that it performs better than alternative DCC models in forecasting conditional correlation in the presence of asymmetric correlation between blocks of asset returns. Empirical results show that the model is able to capture the behavior of some blocks of currencies in Asia in the turbulent years of the late 1990s. The volatilities of the peso-baht and ringgit-SG dollar blocks are positively conditionally correlated. This dynamic conditional correlation rose sharply during the 1997-98 Asian Financial Crisis and is highly persistent but not asymmetric. On the other hand, the conditional correlation of the volatility of HK dollar-yuan block saw periods of high positive and negative dynamic conditional correlations with the peso-baht and ringgit-SG dollar blocks. Furthermore, the dynamic conditional correlation of the volatility of this block is highly asymmetric with the peso-baht and highly persistent with the ringgit-SG dollar especially during the crisis years.

Keywords: asymmetric effect, block dynamic conditional correlation, multivariate GARCH
JEL Codes: C32, E43, G10

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I. Introduction

By now, the GARCH model of Bollerslev (1986) has been extended to several classes of multivariate GARCH models, see Bauwens, Laurent and Rombouts (2006). GARCH itself has come a long way since Robert Engle’s (1982) pioneering paper on the ARCH. Multivariate GARCH research focuses on ways of simplifying the variance-covariance matrix where the number of parameters to be estimated explodes for higher dimensions making estimation costly and computationally intractable. The approaches to simplify the estimation of the parameters of the variance-covariance matrix are now well-developed although suggestions have been made to come up with models that account for economic theory as a basis for simplifying this matrix, Diebold (2004).

It is widely held in financial econometrics that the returns of financial assets move together. The behavior of returns can be investigated using volatility models. Although models of MGARCH have accounted for the stylized fact that similar assets move together there are other salient features of financial assets that need to be accounted for. Dissimilar assets have varying degrees of correlation and one set of assets serves as a leading source of volatility for other sets of assets. Conditional correlation research has gained momentum only in recent years but its unconditional counterpart is the most common input to models being used by a typical investor. Correlations serve as input to optimal portfolio models of equities and also in hedge ratio adjustments.

The different types of financial assets result in certain groups of assets to be more correlated with each other than they are relative to others (see Kroner and Ng (1998), Billio, Caporin and Gobbo (2003)). An example is the property, food and beverage, energy, banking and finance, mining sectors in a stock market. Stock prices within each sector are highly correlated with each other and the degree and direction of correlations between sectors are known to vary. It has been observed that the impact of bad news on stock price correlation is asymmetric between small and large firms. It is greater on small firms when bad news occur with large firms but not vice-versa, Kroner and Ng (1998). This is important in asset allocation where investors decide what proportion of different types of instruments should comprise their portfolio to lower the risk of their overall holdings while at the same time maximize their
returns. This asymmetric behavior when applied to asset allocation modeling leads to economically significant gains in an investor’s portfolio according to Patton (2004).

Asymmetric effect occurs when unexpected downward movements in the price of an asset raise the conditional volatility of returns more than when there are unexpected upward movements (Nelson (1991), Engle and Ng (1993)). This phenomenon was first noted by Black (1976) who found evidence that drops in stock prices result in higher volatility of returns. The asymmetric effect was confirmed by empirical investigations of French, Schwert and Stambaugh (1987), Schwert (1990) and Nelson (1991) among others. In the stock market studies, Erb, Harvey and Viskanta (1994), Ang and Chen (2001), Longin and Solnik (2001) have shown that there is greater dependence between returns during market downturns.

Asymmetric effect in blocks or groups of financial assets were also observed by Lo and MacKinlay (1990) and Conrad, Gultekin and Kaul (1991). The lead-lag effect in portfolio returns by Lo and MacKinlay (1990) says that small firm portfolio returns lag large firm portfolio returns but not the other way around while the volatility spill-over hypothesis by Conrad, Gultekin and Kaul (1991) claims that volatility spills over large to medium and medium to small firms but not the other way round. Milunovich (2003) confirmed these asymmetric behaviors in stock prices of blocks of small, medium and large firms using a structural MGARCH model. In the study of worldwide linkages in the dynamics of volatility and correlations of bonds and equity markets Capiello, Engle and Sheppard (2003) showed that there were strong asymmetries in conditional volatility of equity index returns while bond index returns have little evidence of this behavior.

Capiello, Engle and Sheppard (2003) estimated the correlations stock and bond indices of four major blocks or regions assuming the same dynamic condition for the correlations. On the other hand, Billio, Caporin and Gobbo (2003) introduced Block DCC which assumes different dynamic condition for conditional correlation for assets within a certain group or block of assets. But Billio, Caporin and Gobbo’s (2003) Block DCC does not account for asymmetries between blocks while the Asymmetric DCC model of Capiello, Engle and Sheppard (2003) does not consider the asymmetric correlations between blocks of assets per se. Capiello, Engle and Sheppard (2003) only took the average dynamic correlations of individual indices to represent regional dynamic conditional correlations.
This paper will extend the Block DCC by proposing an Asymmetric Block DCC model of the MGARCH. Billio, Caporin and Gobbo (2003) noted the possible extension of their model that would include an asymmetric component but did not pursue this possibility and thus the motivation for this study.

II. Multivariate GARCH and Conditional Correlations

The general representation of the MGARCH model

\[ y_t = \mu_t(\theta) + \epsilon_t \]
\[ \epsilon_t = H_t^{1/2}(\theta)z_t \text{ where } z_t \sim N(0, I) \]  
\[ \epsilon_t | \mathcal{F}_{t-1} \sim N(0, H_t) \]

where \( y_t \) is the vector of returns and \( \mathcal{F}_{t-1} \) is a sigma algebra of information up to time \( t - 1 \).

Bollerslev, Engle and Wooldridge (1988) argued that it is important to account for the heteroskedastic nature of asset returns in any intertemporal asset pricing model. In their paper, they introduced what became known as the VEC model which is one of the primary MGARCH models. This model specifies each element of \( H_t \) as a linear function of the lagged squared errors and cross products of errors and lagged values of the elements of \( H_t \):

\[ \text{vech}(H_t) = C + \sum_{i=1}^{q} A_i \text{vech}(\epsilon_{t-i}) + \sum_{i=1}^{p} B_j \text{vech}(H_{t-j}). \]  

They concluded that the conditional covariance matrix of the asset returns is strongly autoregressive. The expected return or risk premia for the assets are significantly influenced by the second moment of returns.

Another major model for MGARCH was derived by Engle and Kroner (1995) which was a direct extension of the models of Engle (1982) and Bollerslev (1986) was the BEKK model. Here the variances depends solely on past own squared residuals, and covariances depend solely on past own cross-products of residuals. The BEKK model has
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\[ H_t = C^* C^* + \sum_{k=1}^{K} A_k^* \varepsilon_{t-k} \varepsilon_{t-k} A_k^* + \sum_{k=1}^{K} G_k^* H_{t-1} G_k^* , \]  

(2.3)

where \( C^* , A_k^* \) and \( G_k^* \) are \((N \times N)\) matrices but \( C^* \) is upper triangular. The conditions for \( C^* , A_k^* \) and \( G_k^* \) assures positive definiteness of \( H_t \). Here they presented a parameterization that ensured positive definiteness of \( H_t \). Covariance stationarity was investigated and relationship between the reduced form and structured models was analyzed. These were found particularly useful in financial models such as capital asset pricing and dynamic hedging.

The VEC and BEKK models belong to a class of MGARCH where the conditional variance-covariance structure is simplified through generalization of the conditional variance-covariance matrix. Bauwens, Laurent and Rombouts (2006) provide the most recent and comprehensive survey of the multivariate GARCH models. On the other hand, a nonlinear approach to simplifying the conditional variance-covariance matrix was initiated by Bollerslev (1990) who proposed a multivariate time series model with time-varying conditional variances and covariances with constant conditional correlation (CCC) which largely reduced the number of parameters in the VEC and BEKK models. He has shown that the co-movements of five nominal European-U.S. dollar exchange rates were significantly higher during the implementation of the European Monetary System (EMS) compared to the pre-EMS free-float period. He used well-documented heteroskedastic movement in short-run exchanges which rendered traditional homoskedastic econometric models invalid.

The Bollerslev (1990) CCC MGARCH model has

\[ H_t = D_t R D_t = (h_{ij}) = \left( \rho_{ij} \sqrt{h_{ii} h_{jj}} \right) , \]  

(2.4)

where

\[ D_t = diag\left( h_{11}^{1/2} \ldots h_{Nt}^{1/2} \right) , \]

\( h_{ii} \) can be defined as any univariate GARCH model, and

\[ R_t = (\rho_{ij}) \]

is a symmetric positive definite matrix with \( \rho_{ii} = 1, \forall i \).
Kroner and Ng (1998) noted that the CCC restriction is not valid in most cases and thus the constant assumption of conditional correlation need to be relaxed. Tse and Tsui (2002) have proposed the first time-varying conditional correlation model where

\[ R_t = (1 - \theta_1 + \theta_2)R + \theta_2\psi_{t-1} + \theta_2R_{t-1} \] (2.5)

follows an ARMA analogue. Their varying-correlation or VC MGARCH model result in acceptable parameter estimates for small sample sizes in simulation studies.

On the other hand, Engle (2002) extended the work of Bollerslev (1990) to a dynamic conditional correlation (DCC) model. He has shown that DCC is most often accurate compared to other MGARCH estimators which include the BEKK, Moving Average and the Orthogonal GARCH models.

The Engle (2002) DCC MGARCH model has

\[ H_t = D_t R_t D_t = \left( \rho_{ij} \sqrt{h_{ii} h_{jj}} \right) \] (2.6)

with the proposed dynamic correlation structure

\[ R_t = Q_t^{-1} Q_t^{-1} \] (2.7)

\[ Q_t = \left( 1 - \sum_{m=1}^{M} \alpha_m - \sum_{n=1}^{N} \beta_n \right) \bar{Q} + \sum_{m=1}^{M} \alpha_m (e_{t-m}^* e_{t-m}^*) + \sum_{n=1}^{N} \beta_n Q_{t-n} \] and

\[ Q_t^* = \text{diag}(\sqrt{q_{ii}}) \] (2.8)

where \( \bar{Q} = E[e_t^* e_t^*] \) is the unconditional covariance of standardized residuals of the univariate GARCH models, \( e_t^* \sim N(0,R_t) \) are residuals standardized by their conditional standard deviation, \( \alpha_m \) and \( \beta_n \) are parameters that satisfy the condition of positive definiteness of \( Q_t \) and in effect ensure the positive definiteness of \( R_t \), the proof of which is provided by Engle and Sheppard (2001).

Billio, Caporin and Gobbo (2003, 2004) found the conditions of the DCC-MGARCH model limited since Engle (2002) assumed that the dynamic condition is the same for all correlations. They proposed a Block DCC-MGARCH which allows the dynamic conditions to vary between groups of financial assets and only remain the same within a group. The extension of Billio, Caporin and Gobbo (2003) has the following dynamic condition for the correlations

\[ Q_t = \left( 1 - \alpha(L) - \beta(L) \right) \bar{Q} + \alpha(L)e_t^* e_t^* + \beta(L) Q_t \] (2.10)
\[ \alpha(L) = \sum_{i=1}^{q} \alpha_i L^i \quad \beta(L) = \sum_{j=1}^{p} \beta_j L^j \]

where \( \circ \) indicates the Hadamard product. All the matrices have \( N \times N \) where the \( N \) variables are grouped in \( w \) sets of \( m_1, m_2, \ldots, m_w \)-dimensional vectors. The \( \alpha_i \) and \( \beta_j \) have the following structure

\[
\alpha_i = \begin{bmatrix}
\alpha_{i,11} i(m_1) i(m_1)' & \alpha_{i,12} i(m_1) i(m_2)' & \cdots & \alpha_{i,1w} i(m_1) i(m_w)'
\alpha_{i,21} i(m_2) i(m_1)' & \alpha_{i,22} i(m_2) i(m_2)' & \cdots & \alpha_{i,2w} i(m_2) i(m_w)'
\vdots & \vdots & & \vdots
\alpha_{i,w1} i(m_w) i(m_1)' & \alpha_{i,w2} i(m_w) i(m_2)' & \cdots & \alpha_{i,ww} i(m_w) i(m_w)'
\end{bmatrix}
\]

\[
\beta_j = \begin{bmatrix}
\beta_{j,11} i(m_1) i(m_1)' & \beta_{j,12} i(m_1) i(m_2)' & \cdots & \beta_{j,1w} i(m_1) i(m_w)'
\beta_{j,21} i(m_2) i(m_1)' & \beta_{j,22} i(m_2) i(m_2)' & \cdots & \beta_{j,2w} i(m_2) i(m_w)'
\vdots & \vdots & & \vdots
\beta_{j,w1} i(m_w) i(m_1)' & \beta_{j,w2} i(m_w) i(m_2)' & \cdots & \beta_{j,ww} i(m_w) i(m_w)'
\end{bmatrix}
\]

where \( i(m_g) \) is a column vector of ones with dimension \( m_g \), where \( g = \{1, 2, \ldots, w\} \) and \( L^i \) is the time lag of order \( i \). They have confirmed that indeed there are dissimilarities in the dynamic conditions of the correlations between sectors of Italian stocks. Furthermore, in asset allocation, the Block DCC outperformed the CCC and DCC in terms of returns and optimal portfolio variances.

### III. Asymmetric Block Dynamic Conditional Correlation Model

The dynamic conditional correlation model of Engle (2002) was extended by Cappiello, Engle and Sheppard (2003) to an Asymmetric DCC MGARCH where

\[ Q_t = \left( Q - A' \bar{Q} A - B' \bar{Q} B - G' \bar{N} G \right) + A' \bar{\varepsilon} \bar{\varepsilon} A + B' Q_{t-1} B + G' n_{t-1} n_{t-1}' G. \quad (3.1) \]

\( A \), \( B \) and \( G \) are diagonal parameter matrices. The asymmetric component is \( n_i = I[\varepsilon_i < 0] \circ \varepsilon_i \) where \( \bar{N} = E[n_i, n_i] \). But to account for the asymmetric effect between groups of assets a new model is proposed: the Asymmetric Block DCC MGARCH which has the following innovation of the dynamic conditional correlation
The asymmetric component of this dynamic condition for the correlation matrix is the same as that of Cappiello, Engle and Sheppard (2003), \( n_t = I[\varepsilon_t^* < 0] \circ \varepsilon_t^* \), with \( \alpha(L) \) and \( \beta(L) \) similar to that of Billio, Caporin and Gobbo (2003) and

\[
\eta(L) = \sum_{k=1}^{\tau} \eta_i L_k^\top \quad \text{where}
\]

\[
\eta_k = \begin{bmatrix}
\eta_{k,11}i(m_1)i(m_1)' & \eta_{k,12}i(m_1)i(m_2)' & \cdots & \eta_{k,1w}i(m_1)i(m_w)' \\
\eta_{k,21}i(m_2)i(m_1)' & \eta_{k,22}i(m_2)i(m_2)' & \cdots & \eta_{k,2w}i(m_2)i(m_w)'
\end{bmatrix}.
\]

As in Engle’s (2002) paper, \( \overline{Q} = E[\varepsilon_t^*\varepsilon_t^*'] \) is the unconditional covariance of standardized residuals, \( \varepsilon_t^* \), of the univariate GARCH models where \( \varepsilon_t^* \sim N(0,R_i) \) are standardized by their conditional standard deviations, \( Q_t^* \) is a diagonal matrix, \( Q_t^* = \text{diag}(\sqrt{q_{ii}}) \), consisting of the diagonal elements of \( Q_t \), which ensures \( R_i \) is a correlation matrix. The sample equivalent \( \hat{Q} = \frac{\sum_{t=1}^{T} \varepsilon_t^*\varepsilon_t^*}{T} \) and \( \hat{N} = \frac{\sum_{t=1}^{T} n_t n_i}{T} \) serve as estimators of \( \overline{Q} = E[\varepsilon_t^*\varepsilon_t^*'] \) and \( \overline{N} = E[n_t n_i] \), respectively, where \( T \) is the length of the series. The estimation of the parameter values for the Asymmetric Block DCC model invokes the concept of variance targeting introduced by Engle and Mezrich (1996). Variance targeting assumes that in the long run the variance-covariance matrix, \( Q_t \), approaches the sample variance-covariance matrix.

In order to ensure that the estimation is conducted within the valid parameter space, the Asymmetric Block DCC must be specified by maintaining the positive definiteness of the conditional correlation matrix. The following conditions ensure the positive definiteness of \( Q_t^* \):

C.1 the smallest eigenvalue of \([I - \alpha(L) - \beta(L)] \circ \overline{Q} - \eta(L) \circ \overline{N} \) is greater than 0;

C.2 the smallest eigenvalue of \( \alpha(L) \circ (\varepsilon_t^*\varepsilon_t^*') \) is greater than or equal to 0;

C.3 the smallest eigenvalue of \( \beta(L) \circ Q_t \) is greater than 0; and
C.4 the smallest eigenvalue of \( \eta(L) \circ (n_{i-1} n_i) \) is greater than or equal to 0. 

In the optimization, these conditions make the location of a maximum of the likelihood function difficult. According to Engle and Sheppard (2001), a sufficient but not necessary condition for \( Q \) to be positive definite is for all the parameters to be positive; and a minimum condition to ensure the positive definiteness of \( Q \) is for condition C.1 to be satisfied as shown by Engle and Mezrich (1996).

An alternative Asymmetric Block DCC model is also proposed in this paper and has the following specification for \( Q_i \):

\[
Q_i = (I - \alpha(L) - \beta(L) - \eta(L)) \circ \overline{Q} + \alpha(L) \circ (e_i^* e_i) + \beta(L) \circ Q_i + \eta(L) \circ (n_i n_i)
\]

(3.3)

But this specification no longer satisfies variance targeting. C.1 to C.4 apply to this alternative model in ensuring the positive definiteness of \( Q_i \) where C.1 has \((I - \alpha(L) - \beta(L) - \eta(L)) \circ \overline{Q} \) instead of \([I - \alpha(L) - \beta(L)] \circ \overline{Q} - \eta(L) \circ \overline{N}\).

It is important to discuss the difference of the proposed Asymmetric Block DCC model and its alternative to the following models of Cajigas and Urga (2005):

\[
Q_i = (Q - A'QB - B'QB - G'N G) + A'(e_i^* e_i) A + B' Q_i B + G' (n_i n_i) G,
\]

(3.4)

and

\[
Q_i = (I - A' A - B' B - G' G) \overline{Q} + A'(e_i^* e_i) A + B' Q_i B + G' (n_i n_i) G
\]

(3.5)

where \( A, B \) and \( G \) are diagonal parameter matrices with elements \( a_{ii}, b_{ii} \) and \( g_{ii} \), respectively. The Asymmetric DCC of Cappiello, Engle and Sheppard (2003) is a special case of Equation (3.4) where the elements of \( A, B \) and \( G \) are \( \sqrt{a}, \sqrt{b} \) and \( \sqrt{g} \), respectively. Equation (3.5) is the Asymmetric Generalized DCC model of Cajigas and Urga (2005).

The Asymmetric Block DCC nests the Asymmetric DCC and Equation (3.4) through the following:

a. ADCC, if the elements of the \( \alpha(L), \beta(L) \) and \( \eta(L) \) parameter matrices have \( \alpha_{ii} = a \) for \( \alpha(L) \), \( \beta_{ii} = b \) for \( \beta(L) \), and \( \eta_{ii} = g \) for \( \eta(L) \), for all \( i, j \in \{1, ..., N\} \).
b. Equation (3.4), if the elements of the $\alpha(L), \beta(L)$ and $\eta(L)$ parameter matrices have
\[
\alpha_a = a_a^2 \quad \text{and} \quad \alpha_g = a_g a_{jj} \quad \text{for} \quad \alpha(L), \quad \beta_a = b_a^2 \quad \text{and} \quad \beta_g = b_g b_{jj} \quad \text{for} \quad \beta(L), \quad \eta_a = g_a^2 \quad \text{and} \quad \eta_g = g_g g_{jj} \quad \text{for} \quad \eta(L), \quad \text{for all} \quad i, \, j \in \{1, \ldots, N\} \quad \text{where} \quad i \neq j.
\]
While the alternative Asymmetric Block DCC regresses to the Asymmetric Generalized DCC of Cajigas and Urga (2005) if the conditions in b. are also satisfied.

IV. Parameter Estimation

The likelihood function of the proposed Asymmetric Block DCC MGARCH is derived under the assumption that the underlying distribution of the vector of returns is multivariate normal. Due to the difficulty of maximizing the likelihood function the limited information maximum likelihood (LIML) is utilized to make the estimation of parameter values. LIML is a two-stage parameter estimation procedure where the set of parameters will be divided into two sets. The likelihood function is maximized with respect to the first set of parameters then the parameters estimates of the first set serve as input to the second stage where the next set of parameters are estimated. Pagan (1986) has shown that this procedure for obtaining maximum likelihood estimates is consistent for both stages. The likelihood function for a $N$-variate model, assuming that the underlying distribution of the vector of returns is normal,

\[
L(\vartheta, \phi \mid \gamma_i) = \prod_{t=1}^{T} \left( \frac{1}{\sqrt{2\pi}} \right)^N |H|^{-1/2} e^{-\frac{1}{2} \gamma_i^T H \gamma_i}.
\]  

(4.1)

The vector $\vartheta$ consists of univariate GARCH parameters for each element of the $N$-dimensional $\gamma_i$ vector of returns and vector $\phi$ consists of the parameters of the asymmetric block dynamic correlation structure. Engle and Sheppard (2001) proposed a two-stage parameter estimation procedure for the maximum likelihood function. The vector $\vartheta$ of univariate GARCH parameters are estimated in the first stage and the parameter estimates serve as input to the second stage where the vector $\phi$ of the parameters of the asymmetric dynamic correlation will then be estimated. In their paper, Engle and Sheppard (2001) have shown the consistency and asymptotic normality of this two-stage estimation
procedure. The following shows the parameter estimation of the likelihood function. Taking the natural logarithm of the likelihood function

\[
\log L(\vartheta, \phi \mid y_t) = -\frac{1}{2} N \log(2\pi)^T - \frac{1}{2} \log|H_t|^T + \frac{1}{2} \sum_{i=1}^{T} y_i H_t^{-1} y_i 
\]

\[
= -\frac{1}{2} N \sum_{i=1}^{T} \log(2\pi) - \frac{1}{2} \sum_{i=1}^{T} \log|H_t| + \frac{1}{2} \sum_{i=1}^{T} y_i H_t^{-1} y_i 
\]

\[
= -\frac{1}{2} \sum_{i=1}^{T} \left( N \log(2\pi) + \log|H_t| + y_i H_t^{-1} y_i \right)
\]

Since \( H_t = D_t R_t D_t \) where \( D_t = \text{diag} \left(h_t^{1/2} ... h_t^{1/2} \right) \), we have

\[
\log L(\vartheta, \phi \mid y_t) = -\frac{1}{2} \sum_{i=1}^{T} \left( N \log(2\pi) + \log|D_t R_t D_t| + y_i D_t^{-1} R_t^{-1} D_t^{-1} y_i \right)
\]

\[
= -\frac{1}{2} \sum_{i=1}^{T} \left( N \log(2\pi) + \log|R_t| + 2 \log|D_t| + y_i D_t^{-1} R_t^{-1} D_t^{-1} y_i \right)
\]

As shown by Engle and Sheppard (2001), if \( R_t \) is assumed to be an identity matrix in the first stage estimation,

\[
\log L(\vartheta \mid y_t) = -\frac{1}{2} \sum_{i=1}^{T} \left( N \log(2\pi) + \log|I_N| + 2 \log|D_t| + y_i D_t^{-1} I_N^{-1} D_t^{-1} y_i \right)
\]

\[
\hat{\vartheta} = \arg \max [\log L(\vartheta \mid y_t)]
\]

turns out to be the univariate estimation of the individual GARCH models of the \( N \)-dimensional \( y_t \) vector of returns. The second stage estimation will have

\[
\log L(\phi \mid \hat{\vartheta}, y_t) = -\frac{1}{2} \sum_{i=1}^{T} \left( N \log(2\pi) + \log|R_t| + 2 \log|\hat{D}_t| + y_i \hat{D}_t^{-1} R_t^{-1} \hat{D}_t^{-1} y_i \right)
\]

\[
= -\frac{1}{2} \sum_{i=1}^{T} \left( N \log(2\pi) + \log|R_t| + 2 \log|\hat{D}_t| + \varepsilon_i^{-*} \varepsilon_i^{-*} \right)
\]

where \( \varepsilon_i^{-*} = \hat{D}_t^{-1} y_i \) is the vector of first stage standardized residuals. Since \( R_t = Q_t^{-1} Q_t^{-1} \),

\[
\log L(\phi \mid \hat{\vartheta}, y_t) = -\frac{1}{2} \sum_{i=1}^{T} \left( N \log(2\pi) + \log|Q_t^{-1} Q_t^{-1}| + 2 \log|\hat{D}_t| + \varepsilon_i^{-*} \left(Q_t^{-1} Q_t^{-1}\right)^{-1} \varepsilon_i^{-*} \right)
\]

where \( Q_t^{-1} = \text{diag} \left(\sqrt{q_{it}}\right) \).

Excluding the constant terms in the log likelihood function we have
$$\log L' (\varphi \mid \hat{\varphi}, y_i) = -\frac{1}{2} \sum_{t=1}^{T} \left[ \log |Q_{t}^{-1} Q_{t}^{\ast} Q_{t}^{\ast} | + \varepsilon_t^* (Q_{t}^{-1} Q_{t}^{\ast} Q_{t}^{\ast})^{-1} \varepsilon_t^* \right]$$

(4.8)

$$\hat{\varphi} = \arg \max [\log L' (\varphi \mid \hat{\varphi}, y_i)]$$

(4.9)

where $Q_t = (\overline{Q} - \alpha(L) \odot \overline{Q} - \beta(L) \odot \overline{Q} - \eta(L) \odot \overline{N}) + \alpha(L) \odot (\varepsilon_t^\ast \varepsilon_t^\ast) + \beta(L) \odot Q_t + \eta(L) \odot (n, n_\ast)$. 

Expanding the 2nd stage log likelihood function

$$\log L' (\varphi \mid \hat{\varphi}, y_i)$$

(4.10)

$$= -\frac{1}{2} \sum_{t=1}^{T} \left\{ \log |Q_{t}^{-1} (\overline{Q} - \alpha(L) \odot \overline{Q} - \beta(L) \odot \overline{Q} - \eta(L) \odot \overline{N}) + \alpha(L) \odot (\varepsilon_t^\ast \varepsilon_t^\ast) + \beta(L) \odot Q_t + \eta(L) \odot (n, n_\ast) \} | Q_{t}^{-1} \right\}$$

$$+ \varepsilon_t^* (Q_{t}^{-1} (\overline{Q} - \alpha(L) \odot \overline{Q} - \beta(L) \odot \overline{Q} - \eta(L) \odot \overline{N}) + \alpha(L) \odot (\varepsilon_t^\ast \varepsilon_t^\ast) + \beta(L) \odot Q_t + \eta(L) \odot (n, n_\ast) \} Q_{t}^{-1} \right\}^{-1} \varepsilon_t^* \right\}$$

which is a long expression and tedious for large dimensional vector of returns.

In the optimization process the variance targeting constraint of Engle and Mezrich (1996) is invoked.

V. Simulation Results

Monte Carlo simulations were done to determine the consistency of the MLE estimator as the sample size is increased for the Asymmetric Block DCC in the case of a 4-dimensional vector return series, partitioned into two 2-dimensional vectors where lag orders $\overline{q}, \overline{p}$ and $\overline{r}$ of $L$ are all equal to 1 or ABDCC(2,2;1,1,1). The general notation of the model is $\text{ABDCC}(m_\ast, \ldots, m_\ast; \overline{p}, \overline{q}, \overline{r})$. The univariate conditional variances are generated by two highly persistent and two less persistent volatility series:

$$h_{11,\text{init},t} = 0.05 + 0.05 \varepsilon_{1,\text{init},t-1}^2 + 0.90 h_{11,\text{init},t-1}$$

$$h_{22,\text{init},t} = 0.10 + 0.07 \varepsilon_{2,\text{init},t-1}^2 + 0.85 h_{22,\text{init},t-1}$$

$$h_{33,\text{init},t} = 0.30 + 0.20 \varepsilon_{3,\text{init},t-1}^2 + 0.55 h_{33,\text{init},t-1}$$

$$h_{44,\text{init},t} = 0.40 + 0.17 \varepsilon_{4,\text{init},t-1}^2 + 0.60 h_{44,\text{init},t-1}$$

The innovation process, $Q_t$, is specified by the following parameters:
which indicate that the first block is highly persistent while the second is not. The between block impact, persistence and asymmetric effect parameters are specified as 0.05, 0.40 and 0.05, respectively.

Table 1 summarizes the bias and MSE of the estimates for all the parameters for series lengths of 500, 1,000, and 1,500 for 500 Monte Carlo runs. As the sample size is increased the resulting bias of the estimates is mixed for the different parameters although the magnitudes of the bias for all the parameters are tolerable. This is expected for parameters that are constrained to be in the parameter space \( \Theta \) where \( \Theta \in (0,1) \). Engle and Sheppard (2001) placed such constraint as a sufficient condition for the innovation process, \( Q_t \), to remain positive definite. The MSE generally improved for all the parameters as the sample size is increased and confirms the consistency of the maximum likelihood estimator for the model.

In order to assess how well the ABDCC model fits the conditional correlation between blocks of assets where the asymmetry of conditional correlation between blocks exists and to compare its performance vis-à-vis the other dynamic conditional correlations models: DCC, BDCC, ADCC, AGDCC, some cases of asymmetric block dynamic correlations were simulated. Below are specifications for three cases: nonpersistent-nonpersistent, persistent-nonpersistent and persistent-persistent conditional correlations between blocks of assets for a series of 1,000 observations. For each case, 500 Monte Carlo runs were made.

**Case 1:**

\[
\begin{align*}
\alpha_{11} &= 0.07 & \alpha_{22} &= 0.06 & \alpha_{12} = \alpha_{21} &= 0.04 \\
\beta_{11} &= 0.51 & \beta_{22} &= 0.58 & \beta_{12} = \beta_{21} &= 0.45 \\
\eta_{11} &= 0.04 & \eta_{22} &= 0.04 & \eta_{12} = \eta_{21} &= 0.03
\end{align*}
\]
Case 2:

\[ h_{11,t} = 0.05 + 0.05 \varepsilon_{1,t-1}^2 + 0.80 h_{11,t-1} \]
\[ h_{22,t} = 0.10 + 0.07 \varepsilon_{2,t-1}^2 + 0.75 h_{22,t-1} \]
\[ h_{33,t} = 0.30 + 0.20 \varepsilon_{3,t-1}^2 + 0.55 h_{33,t-1} \]
\[ h_{44,t} = 0.40 + 0.17 \varepsilon_{4,t-1}^2 + 0.60 h_{44,t-1} \]
\[ \alpha_{11} = 0.15 \quad \alpha_{22} = 0.12 \quad \alpha_{12} = \alpha_{21} = 0.05 \]
\[ \beta_{11} = 0.60 \quad \beta_{22} = 0.50 \quad \beta_{12} = \beta_{21} = 0.40 \]
\[ \eta_{11} = 0.05 \quad \eta_{22} = 0.05 \quad \eta_{12} = \eta_{21} = 0.05 \]

Case 3:

\[ h_{11,t} = 0.05 + 0.06 \varepsilon_{1,t-1}^2 + 0.90 h_{11,t-1} \]
\[ h_{22,t} = 0.10 + 0.08 \varepsilon_{2,t-1}^2 + 0.85 h_{22,t-1} \]
\[ h_{33,t} = 0.08 + 0.20 \varepsilon_{3,t-1}^2 + 0.68 h_{33,t-1} \]
\[ h_{44,t} = 0.11 + 0.17 \varepsilon_{4,t-1}^2 + 0.72 h_{44,t-1} \]
\[ \alpha_{11} = 0.05 \quad \alpha_{22} = 0.15 \quad \alpha_{12} = \alpha_{21} = 0.05 \]
\[ \beta_{11} = 0.82 \quad \beta_{22} = 0.65 \quad \beta_{12} = \beta_{21} = 0.55 \]
\[ \eta_{11} = 0.07 \quad \eta_{22} = 0.08 \quad \eta_{12} = \eta_{21} = 0.06 \]

Additional Cases 4, 5 and 6 have stronger between block asymmetries, \( \eta_{12} \), of 0.12, 0.15 and 0.15, respectively. Table 2 shows the comparison of the different models in capturing the simulated conditional correlations between two blocks of asset returns. These are in-sample forecasts. The results show that the ADCC of Cappiello, Engle and Sheppard (2003) out-performed all the other DCC models in terms of the lowest root mean squared error (RMSE) criterion. The ABDCC comes in second for Cases 2 to 6. DCC did better over ABDCC in Case 1. For cases with persistent conditional correlations, especially those with high asymmetry, the performance of ABDCC is better than DCC. The AGDCC has the worst performance in all cases which can be explained by the restrictiveness of its parameter specification relative to the other models.

Taking ADCC and ABDCC as the two best alternatives, 500 Monte Carlo runs of 200-step out-of-sample forecast was done for each of these two models. Table 3 summarizes the results of the out-of-
sample forecast performance of ADCC and ABDCC in estimating the dynamic conditional correlation of two blocks of assets with asymmetry generated by the same process as Cases 1 to 6. The mean squared error criterion was used to compare the two forecasts. In all cases, the ABDCC has a lower average MSE in 200-step out-of-sample forecast of 500 Monte Carlo runs. To test whether there is a significant difference in forecast accuracy, the Diebold and Mariano (1995) test or DM test for forecasting accuracy and the modified DM test (MDM) of Harvey, Leybourne and Newbold (1997) were used to evaluate the performance of these two tests. Table 3 shows the proportion of rejection of the null hypothesis for each test out of the 500 Monte Carlo runs. Eighty-three to 97 percent of the 500 runs results in the rejection of the null hypothesis of equal forecast accuracy using the DM and MDM tests. These means that the two models differ in forecast accuracy and confirms that ABDCC has a significantly lower MSE compared to ADCC in all cases considered.

VI. Empirical Example

The ABDCC is applied to some Asian currencies. The data was derived from FXHistory in oanda.com. These are 1,279 daily average exchange rates with respect to the U.S. dollar from 1996 to 2000 of the Philippine peso (PHP), Thailand baht (THB), Malaysian ringgit (MYR), Singapore dollar (SGD), Hong Kong dollar (HKD) and China yuan (CNY). Adjustments have been made to account for holidays. An ABDCC(2,2;1,1,1) was used to model the following blocks: PHP-THB, MYR-SGD and HKD-CNY. The Philippine peso and Thailand baht are considered as a block because these two economies are regarded as “twins” in the ASEAN. On the other hand, Malaysian ringgit and Singaporean dollar are in another block given that these two economies are relatively more developed compared to Philippines and Thailand. Hong Kong dollar and Chinese yuan belong to a block for these two economies are reasonably linked since Hong Kong became a special administrative region of China in July of 1997.

Table 4, 5 and 6 show the conditional correlations of the blocks of currencies. All the parameters are significant at the 0.05 level except for the asymmetric parameter between the PHP-THB and MYR-SGD blocks as shown in Table 4. This implies that there is no significant asymmetric correlation in the volatilities of the peso-baht and ringgit-SG dollar although the conditional correlations are highly persistent between these two blocks. Asymmetry in conditional correlations is present for these two
blocks when compared with the HK dollar-yuan block as presented in Tables 5 and 6. Table 6 further shows that the correlation of volatility is persistent between HK dollar-yuan and ringgit-SG dollar owing largely to the level of development and relative stability of the financial markets in Hong Kong and Singapore while HK dollar-yuan and peso-baht correlation of volatility are not as persistent. There is also a higher asymmetry in the conditional correlation of HK dollar-yuan and peso-baht.

To present the asymmetric block DCC between blocks, the estimated conditional variance, $\hat{q}_{ij}$, within a block were pooled to get the pooled conditional variance within a block. The pooled conditional covariance was also computed for the between blocks. Figures 1, 2 and 3 show the conditional correlations between blocks. The asymmetric block DCC is clearly positive for the peso-baht and ringgit-SG dollar in Figure 1 for the period considered which indicate the linkage of the economies of these four ASEAN countries. At the same time, there was a sharp rise in the conditional correlation of the two blocks during the 1997-98 Asian Financial Crisis. The drop in the conditional correlation occurred in September of 1998 when Malaysia pegged its exchange rate to discourage speculators against its currency. In Figure 2 and 3, the conditional correlations of peso-baht and ringgit-SG dollar against HK dollar-yuan is fluctuating around zero which indicate periods of positive and negative conditional correlations. But in Figure 3 the 1997-98 period resulted in higher volatility of the conditional correlation between ringgit-SG dollar and HK dollar-yuan and this volatility in conditional correlation relatively mellowed after 1998 when the ringgit exchange rate was pegged and the SG-dollar has stabilized. This is dissimilar to the pattern between peso-baht and HK dollar-yuan where the relatively stable exchange rates of the HK dollar and the yuan are fluctuating similarly across the period against the peso-baht.

The significant asymmetries of the ASEAN blocks with respect to the HK dollar-yuan block may be explained by the relatively stable movement of these two currencies compared to their ASEAN counterparts in the period considered. The insignificant asymmetry between the ASEAN blocks implies that although the correlation of the volatilities of the peso-baht and the ringgit-SG dollar is persistent there is no asymmetric effect observed in the dynamic conditional correlation of the volatility of the two blocks.
VII. Conclusion

The Asymmetric Block Dynamic Conditional Correlation model, a new model which extends the Block DCC of Billio, Caporin and Gobbo (2003), introduces the asymmetric effect in the innovation process between blocks of financial asset returns. The two-stage maximum likelihood estimation procedure utilizing the limited information maximum likelihood approach of Pagan (1986) is shown to be consistent in estimating the parameters of the ABDCC model. It was also shown that the ABDCC is better compared to other DCC models in forecasting conditional correlation in the presence of asymmetric effect in the dynamic conditional correlation between blocks of asset returns.

The model was able to capture the behavior of the six Asian currencies considered to reflect the turbulent times of the Asian Financial Crisis in 1997-98. The peso-baht and ringgit-SG dollar blocks are positively conditionally correlated, this conditional correlation rose sharply during the 1997-98 Asian Financial Crisis. The conditional correlation of peso-baht and ringgit-SG dollar blocks volatilities is highly persistent but not asymmetric which confirms the linkage of these ASEAN currencies. On the other hand, the HK dollar-yuan block saw periods of highly positive and highly negative conditional correlation with respect to the peso-baht and ringgit-SG dollar blocks and the model has shown the presence of asymmetry in the block volatilities of the HK dollar-yuan with the ASEAN blocks. Also, the volatility of the HK dollar-yuan is highly asymmetric against the peso-baht and highly persistent with the ringgit-SG dollar. The conditional correlation between the HK dollar-yuan and ringgit-SG dollar blocks are especially high during the crisis years.

References


### Table 1 – Monte Carlo Simulation Results for Varying Sample Sizes of ABDCC(2,2;1,1,1) Model

<table>
<thead>
<tr>
<th>Block</th>
<th>Actual Value</th>
<th>Series Length</th>
<th>Bias</th>
<th>MSE</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Within Block 1</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\alpha_{11}$</td>
<td>0.15</td>
<td>500</td>
<td>-0.06870</td>
<td>0.00635</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1000</td>
<td>-0.07069</td>
<td>0.00608</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1500</td>
<td>-0.06961</td>
<td>0.00578</td>
</tr>
<tr>
<td>$\beta_{11}$</td>
<td>0.80</td>
<td>500</td>
<td>-0.04274</td>
<td>0.01513</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1000</td>
<td>-0.04472</td>
<td>0.01264</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1500</td>
<td>-0.04528</td>
<td>0.01206</td>
</tr>
<tr>
<td>$\eta_{11}$</td>
<td>0.05</td>
<td>500</td>
<td>-0.01456</td>
<td>0.00160</td>
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<tr>
<td></td>
<td></td>
<td>1000</td>
<td>-0.01738</td>
<td>0.00152</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1500</td>
<td>-0.01910</td>
<td>0.00155</td>
</tr>
<tr>
<td><strong>Within Block 2</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\alpha_{22}$</td>
<td>0.12</td>
<td>500</td>
<td>-0.02797</td>
<td>0.00451</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1000</td>
<td>-0.02762</td>
<td>0.00394</td>
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<td></td>
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<td>1500</td>
<td>-0.03014</td>
<td>0.00315</td>
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<tr>
<td>$\beta_{22}$</td>
<td>0.50</td>
<td>500</td>
<td>-0.03538</td>
<td>0.00837</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1000</td>
<td>-0.02795</td>
<td>0.00797</td>
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<tr>
<td></td>
<td></td>
<td>1500</td>
<td>-0.01957</td>
<td>0.00740</td>
</tr>
<tr>
<td>$\eta_{22}$</td>
<td>0.05</td>
<td>500</td>
<td>-0.02044</td>
<td>0.00166</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1000</td>
<td>-0.02407</td>
<td>0.00163</td>
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<tr>
<td></td>
<td></td>
<td>1500</td>
<td>-0.02842</td>
<td>0.00163</td>
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<tr>
<td><strong>Between Blocks 1 &amp; 2</strong></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\alpha_{12}$</td>
<td>0.05</td>
<td>500</td>
<td>-0.02144</td>
<td>0.00127</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1000</td>
<td>-0.01899</td>
<td>0.00110</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1500</td>
<td>-0.01607</td>
<td>0.00098</td>
</tr>
<tr>
<td>$\beta_{12}$</td>
<td>0.40</td>
<td>500</td>
<td>-0.00273</td>
<td>0.00953</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1000</td>
<td>-0.00949</td>
<td>0.00938</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1500</td>
<td>-0.01532</td>
<td>0.00915</td>
</tr>
<tr>
<td>$\eta_{12}$</td>
<td>0.05</td>
<td>500</td>
<td>-0.00862</td>
<td>0.00159</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1000</td>
<td>-0.01059</td>
<td>0.00136</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1500</td>
<td>-0.01023</td>
<td>0.00127</td>
</tr>
</tbody>
</table>

### Table 2 – RMSE of the Different DCC Models in 500 Monte Carlo Simulations of In-Sample Forecasts in Estimating Simulated Block DCC with Asymmetry

<table>
<thead>
<tr>
<th>Case</th>
<th>DCC(1,1)</th>
<th>BDCC(2,2;1,1)</th>
<th>ADCC(1,1,1)</th>
<th>AGDCC(2,2;1,1,1)</th>
<th>ABDCC(2,2;1,1,1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.01823</td>
<td>0.02086</td>
<td>0.01578</td>
<td>0.08666</td>
<td>0.02047</td>
</tr>
<tr>
<td>2</td>
<td>0.02144</td>
<td>0.02518</td>
<td>0.01745</td>
<td>0.08775</td>
<td>0.02130</td>
</tr>
<tr>
<td>3</td>
<td>0.02575</td>
<td>0.02800</td>
<td>0.01971</td>
<td>0.09084</td>
<td>0.02298</td>
</tr>
<tr>
<td>4</td>
<td>0.04366</td>
<td>0.04145</td>
<td>0.02281</td>
<td>0.07186</td>
<td>0.02448</td>
</tr>
<tr>
<td>5</td>
<td>0.04893</td>
<td>0.04537</td>
<td>0.02602</td>
<td>0.07537</td>
<td>0.02701</td>
</tr>
<tr>
<td>6</td>
<td>0.05353</td>
<td>0.04913</td>
<td>0.02926</td>
<td>0.08230</td>
<td>0.02932</td>
</tr>
</tbody>
</table>

All bold RMSEs are the two lowest.
Table 3 – Proportion of H₀ Rejections in 500 Monte Carlo Simulations of 200-Step Out-of-Sample Forecasts of ADCC and ABDCC in Estimating Simulated Block DCC with Asymmetry

<table>
<thead>
<tr>
<th>Case</th>
<th>MSE</th>
<th>DM Test</th>
<th>MDM Test</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>ADCC</td>
<td>ABDCC</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>0.000455</td>
<td>0.000443</td>
<td>0.900</td>
</tr>
<tr>
<td>2</td>
<td>0.000478</td>
<td>0.000477</td>
<td>0.900</td>
</tr>
<tr>
<td>3</td>
<td>0.000878</td>
<td>0.000535</td>
<td>0.828</td>
</tr>
<tr>
<td>4</td>
<td>0.001021</td>
<td>0.000596</td>
<td>0.966</td>
</tr>
<tr>
<td>5</td>
<td>0.001112</td>
<td>0.000719</td>
<td>0.942</td>
</tr>
<tr>
<td>6</td>
<td>0.002071</td>
<td>0.000830</td>
<td>0.830</td>
</tr>
</tbody>
</table>

Table 4 – ABDCC(2,2;1,1,1) Model of PHP-THB and MYR-SGD Forex Returns

<table>
<thead>
<tr>
<th>Block ^α (s.e.)</th>
<th>PHP-THB ^β (s.e.)</th>
<th>MYR-SGD ^η (s.e.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>^α</td>
<td></td>
<td></td>
</tr>
<tr>
<td>^β</td>
<td>0.164128 (0.002960)</td>
<td>0.041819 (0.000753)</td>
</tr>
<tr>
<td>^η</td>
<td>0.523677 (0.003629)</td>
<td>0.824190 (0.002214)</td>
</tr>
<tr>
<td>^β</td>
<td>0.046345 (0.003323)</td>
<td></td>
</tr>
<tr>
<td>^η</td>
<td>0.041819 (0.000753)</td>
<td></td>
</tr>
</tbody>
</table>

All bold parameter estimates are significant at the 0.05 level.
### Table 5 – ABDCC(2,2;1,1,1) Model of PHP-THB and HKD-CNY Forex Returns

<table>
<thead>
<tr>
<th>Block</th>
<th>PHP-THB</th>
<th>HKD-CNY</th>
</tr>
</thead>
<tbody>
<tr>
<td>^α (s.e.)</td>
<td>0.126281 (0.002443)</td>
<td>0.207637 (0.002027)</td>
</tr>
<tr>
<td>^β (s.e.)</td>
<td>0.510580 (0.008824)</td>
<td>0.501463 (0.001917)</td>
</tr>
<tr>
<td>^η (s.e.)</td>
<td>0.124693 (0.000132)</td>
<td>0.219513 (0.000512)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Block</th>
<th>PHP-THB</th>
<th>HKD-CNY</th>
</tr>
</thead>
<tbody>
<tr>
<td>HKD-CNY</td>
<td>0.195552 (0.002426)</td>
<td>0.482574 (0.003070)</td>
</tr>
<tr>
<td></td>
<td>0.119230 (0.000485)</td>
<td>0.118465 (0.000325)</td>
</tr>
</tbody>
</table>

All bold parameter estimates are significant at the 0.05 level.

### Table 6 – ABDCC(2,2;1,1,1) Model of HKD-CNY and MYR-SGD Forex Returns

<table>
<thead>
<tr>
<th>Block</th>
<th>HKD-CNY</th>
<th>MYR-SGD</th>
</tr>
</thead>
<tbody>
<tr>
<td>^α (s.e.)</td>
<td>0.150419 (0.000233)</td>
<td>0.238101 (0.000199)</td>
</tr>
<tr>
<td>^β (s.e.)</td>
<td>0.574708 (0.000624)</td>
<td>0.683436 (0.000378)</td>
</tr>
<tr>
<td>^η (s.e.)</td>
<td>0.194977 (0.001349)</td>
<td>0.118465 (0.000325)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Block</th>
<th>HKD-CNY</th>
<th>MYR-SGD</th>
</tr>
</thead>
<tbody>
<tr>
<td>MYR-SGD</td>
<td>0.119230 (0.000485)</td>
<td>0.570860 (0.000473)</td>
</tr>
<tr>
<td></td>
<td>0.087742 (0.000376)</td>
<td></td>
</tr>
</tbody>
</table>

All bold parameter estimates are significant at the 0.05 level.
Figure 1 – Asymmetric Block DCC of PHP-THB and MYR-SGD Blocks of Forex Returns

![Graph showing the Asymmetric Block DCC of PHP-THB and MYR-SGD Blocks of Forex Returns from 1996 to 2000.](image)

Figure 2 – Asymmetric Block DCC of PHP-THB and HKD-CNY Blocks of Forex Returns

![Graph showing the Asymmetric Block DCC of PHP-THB and HKD-CNY Blocks of Forex Returns from 1996 to 2000.](image)
**Figure 3** – Asymmetric Block DCC of HKD-CNY and MYR-SGD Blocks of Forex Returns