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Abstract

The paper models the dynamic conditional correlations in emerging stock, bond and foreign exchange markets using the DCC model of Engle (2002) and the GARCC model of McAleer et al. (2008). The highly restrictive DCC model suggests that the conditional correlations of the overall returns are constant. In contrast, the GARCC model finds that the conditional correlations between bond-bond markets and between stock-stock markets are relatively constant across developed-emerging markets, while those between emerging-emerging markets are dynamic. The conditional correlations between stock-bond markets across developed-emerging markets are also more dynamic as compared with those between emerging-emerging markets.

Keywords: Risk, conditional correlations, emerging markets, stocks, bonds, foreign exchange markets.

JEL Classifications: G10, G11, G15, G19.

1. Introduction

A useful method of evaluating portfolio risk is to examine the conditional covariance matrix of the portfolio. This can be achieved by modelling the conditional covariance matrix directly, or by decomposing the covariance matrix into the conditional variance of each asset and their conditional correlations. Although the latter approach is more popular, the strong restriction of constant conditional correlations is typically imposed. Several papers have found that the conditional correlations are not constant over time. Longin and Solnik (2001) found that equity correlations increase (decrease) during bear (rally) markets. Solnik et al. (1996) found that the US and other major bond market returns correlations are not constant, but are influenced by fundamentals and market conditions. Cappiello et al. (2003) found evidence that conditional correlations between equity and bond returns typically decline when stock markets suffer from financial turmoil.

As the construction of an efficient portfolio relies on correlations that can change over time, it is imperative to model the dynamic conditional correlations across financial assets. The dynamics of conditional correlations are also important in constructing multivariate models that incorporate mean and volatility spillovers, as these can lead to more robust parameter estimates if such spillovers are significant.

The paper estimates two dynamic conditional correlation models, the DCC model of Engle (2002) and the GARCC model of McAleer et al. (2006). Such empirical findings should contribute to the literature that has tended to focus on multivariate models that assume constant conditional correlations. The assets of interest are stocks, bonds and foreign exchange rates. The importance of these assets in portfolio construction has been widely documented (see, for example, Hakim and McAleer (2007)). The paper investigates the link between emerging markets (Indonesia, Malaysia, Thailand and the Philippines), and two developed markets as benchmarks (Japan and USA).

The remainder of the paper is as follows. Section 2 provides a brief literature review. The financial econometric methods are discussed in Section 3, the data are presented in Section 4, the empirical results are analysed in Section 5, and some concluding remarks are given in Section 6.

2. Literature Review

Multivariate GARCH models have been used widely to model the linkages across financial assets. Several well-known multivariate GARCH specifications are the Vech model of Bollerslev et al. (1988), the Constant Conditional Correlation (CCC) model of Bollerslev (1990), the BEKK model of Engle and Kroner (1995), the VARMA-GARCH model of Ling and McAleer (2003), and the VARMA-AGARCH model of McAleer et al. (2009).

The assumption of constant conditional correlations implies that the standardized shocks are uncorrelated with their previous values. It is a valid assumption if the standardized shock is a sequence of i.i.d. random vectors, or alternatively a martingale difference process. As the shocks are not likely to be independent, in practice, there is no guarantee that models which impose these restrictions will be valid (for further details, see McAleer (2005) and Caporin and McAleer (2009)). Several papers have found the possibility of dynamic conditional correlations across assets, such as Joy et al. (1976) and Longin and Solnik (1995). The BEKK model of Engle and Kroner (1995) also implies time-varying conditional correlations.

Several papers incorporate time-varying conditional correlations. The DCC model of Engle (2002) investigates the conditional correlations in stock, bond, and foreign exchange markets in USA and France. The model has been applied in several asset interactions, such as the conditional correlations across stock markets by Billio et al. (2004); across stock and foreign exchange markets by Kuper and Lestano (2006); and across bond and stock markets by Dean and Faff (2001). These authors find evidence of time-varying conditional correlations. Tse and Tsui (2002) provide evidence of time-varying conditional correlations between stock and foreign exchange markets using the Varying Conditional Correlation (VCC) model. Using the recently proposed GARCC model, McAleer et al. (2008) find evidence of dynamic conditional correlations, both between the US and Japan stock markets, and between the US and Hong Kong stock markets.

3. Methods

The DCC model of Engle (2002) provides an overall estimate of the dynamic conditional correlations in all assets, whereas the GARCC model of McAleer et al. (2008) provides estimates of the dynamic conditional correlations between pairs of assets. However, the DCC and GARCC models used in the paper do not incorporate conditional mean or volatility spillovers.

The DCC model was designed to allow for two-stage estimation of the conditional covariance matrix, H_t. In the first stage, univariate volatility models are fitted for each of the assets, and estimates of h_t are obtained. At the second stage, asset returns are transformed by the estimated standard deviations from the first stage, and are then used to estimate the parameters of the dynamic conditional correlations.

The DCC model can be written as follows:

$$y_t \left| \Im_{t-1} \sim (0, Q_t), \qquad t = 1,...,T \right. \tag{1}$$

$$Q_t = D_t \Gamma_t D_t, \tag{2}$$

where $D_t = diag(h_{1t},...,h_{kt})$ is a diagonal matrix of conditional variances, and $\Im_t$ is the information set available to time t. The conditional variance is assumed to follow a univariate GARCH model, as follows:

$$h_{it} = \omega_i + \sum_{p=1}^{P_i} \alpha_{ip} \varepsilon_{it-p}^2 + \sum_{q=1}^{Q_i} \beta_{iq} h_{it-p}. \tag{3}$$

When the univariate volatility models have been estimated, the standardized residuals, $\eta_{it} = y_{it} / \sqrt{h_{it}}$, are used to estimate the dynamic conditional correlations, as follows:

$$Q_t = (1 - \phi_1 - \phi_2) S + \phi_1 \eta_{t-1} \eta_{t-1}^{'} + \phi_2 Q_{t-1} \tag{4}$$

$$\Gamma_t = \left\{ (diagQ_t)^{-1/2} \right\} Q_t \left\{ (diagQ_t)^{-1/2} \right\}, \tag{5}$$

where equation (5) is used to standardise the matrix estimated in (4) to satisfy the definition of a correlation matrix.

Denote $E_{t-1}(Y_t) = E\ (Y_t | \Im_{t-1})$ as the expectation of Y_t conditional on the information set, $\Im_{t-1}$. The GARCC model of McAleer et al. (2008) is given as follows:

$$
\begin{gathered}
Y_t = E(y_t | \Im_{t-1};\theta) + \varepsilon_t, \qquad t = 1,...,T \\
\varepsilon_t = D_t^{1/2}\eta_t, \\
D_t = diag(h_{1t},...,h_{kt}), \\
\eta_t = v_t(\eta_{1t},...,\eta_{kt})', \qquad v_t \sim iid(0,1) \\
H_t = W + \sum_{i=1}^{r} A_i \vec{\varepsilon}_{t-1} + \sum_{j=1}^{s} B_j H_{t-j} \\
\eta_{it} = \sum_{l=1}^{L} \phi_{ilt}\eta_{it-l} + \xi_{it}, \qquad \forall\, i = 1,...,k \\
\xi_{it} \sim iid(0,1), \qquad \xi_t \sim iid(0,\Omega) \\
E_{t-1}(\eta_t\eta_t') = Q_t \\
\Gamma_t = diag\{Q_t\}^{-1/2} Q_t diag\{Q_t\}^{-1/2},
\end{gathered} \tag{6}
$$

where $\theta \in \mathbb{R}^a$ is the parameter vector for the conditional first moment, a is the number of elements in θ, and $diag\{A\}$ is a diagonal matrix consisting of the diagonal elements of matrix A.

The dynamic conditional correlations depend on the specifications of ϕ_{ilt} and L. McAleer et al. (2008) consider four specific cases of the GARCC model. This paper considers only the general Case 4 of the GARCC model, which models the dynamic conditional correlations across all pairs of assets. Under Case 4, the conditional correlation matrix can be described by the following process:

$$Q_t = \Omega + \Phi_1 \circ \eta_{t-1}\eta_{t-1}^{'} + \Phi_2 \circ Q_{t-1}. \qquad (7)$$

The Hadamard (or element-by-element product) in (7) captures the dynamics for each pair of conditional correlations in the stock, bond and foreign exchange markets.

4. Data

The data used in the paper are the daily closing price index of bonds, stocks, and foreign exchange rates. The assets returns and their variable names are summarized in Table 1. All the data are obtained from the DataStream and Bloomberg database services. The sample ranges from 28/3/2003 to 8/9/2006, with 901 observations for each index and foreign exchange rate.

The returns of asset i at time t are calculated as $R_{i,t} = \log(P_{i,t} / P_{i,t-1})$, where $P_{i,t}$ and $P_{i,t-1}$ are the closing prices of asset i at days t and $t-1$, respectively. Each stock and bond price index is denominated in the local currency. The data appear to be stationary, based on both the ADF and Phillips-Perron tests. The J-B test of normality suggests that the returns are not normally distributed.

5. Empirical Results

The DCC model of Engle (2002) is estimated to determine the coefficient of the conditional correlations for all returns on a mean basis. In order to determine the coefficient of conditional correlation between all pairs of returns, the GARCC model of McAleer et al. (2008) is also estimated.

Both the DCC and GARCC models are assumed to have the same univariate conditional mean and variance models, namely ARMA(1,1)-GARCH(1,1) as follows:

$$y_{it} = \theta_{i0} + \theta_{i1} y_{it-1} + \theta_{i2} \varepsilon_{it-1} + \varepsilon_{it} \qquad (8)$$

$$\varepsilon_{it} = \eta_{it} \sqrt{h_{it}} \qquad (9)$$

$$h_{it} = \omega_i + \alpha_i \varepsilon_{it-1}^2 + \beta_i h_{it-1}. \qquad (10)$$

The estimates of the parameters in equations (8) and (10) are given in Table 2. In order to check the structural properties of the those models, the second moment and log-moment conditions are evaluated for the ARMA(1,1)-GARCH(1,1) model. Ling and McAleer (2003) showed that the QMLE for the GARCH(1,1) model is consistent if the second moment regularity condition, namely $\alpha_i + \beta_i < 0$ in equation (8), is satisfied. Jeantheau (1988) showed that the weaker log-moment regularity condition, given by $E(\log(\alpha_i \eta_{it}^2 + \beta_i)) < 0$, is sufficient for the Quasi Maximum Likelihood Estimator (QMLE) to be consistent for the GARCH(1,1) model.

Table 2 provides the results of the second moment and log-moment conditions for the GARCH(1,1) model for all returns series. The second moment condition is satisfied for all returns, except for Indbond, Malbond, and Usdmyr. However, the log-moment conditions are satisfied for all series, which suggest that the empirical estimates are statistically valid for these series.

From the mean equation in Table 2, it is clear that not all of the returns are influenced by their own lagged values, which suggests the possibility of impacts from other markets. From the variance equation in Table 2, all returns exhibit significant short and long run persistence, except for Usdjpy, which shows only long run persistence.

The estimated parameters of the conditional correlations for the DCC model are given in Table 3. It is evident that neither estimated coefficient is significant, suggesting that, on average, the conditional correlations of the overall returns are not dynamic. In particular, the impact of news via the standardized residuals is negligible.

In order to accommodate the conditional correlations between any pairs of asset markets, the GARCC model is estimated, for which the empirical results are given in Table 4. The table shows that 38% of pairs of returns (52 of 136) show dynamic conditional correlations, even though some of them display only short or long run dynamics. The evidence of dynamic conditional correlations within the same classes of assets is as follows: (1) between bond markets: 2 of 15 pairs (13%); (2) between stock markets: 4 of 15 pairs (27%); and (3) between foreign exchange markets: 6 of 10 pairs (60%). It can be concluded that between the same classes of assets, the dynamic conditional correlations between foreign exchange markets have the most significant dynamics, followed by the dynamic conditional correlations between stock markets and between bond markets.

The evidence of dynamic conditional correlations across different classes of assets is as follows. (1) between bond and stock markets: 11 of 36 pairs (31%); (2) between bond and foreign exchange markets: 12 of 30 pairs (40%); and (3) between stock and foreign exchange markets: 15 of 30 pairs (50%). This suggests that, across different classes of assets, the conditional correlations between stock and foreign exchange markets are the most dynamic, followed by the conditional correlations between bond and foreign exchange markets, and between bond and stock markets.

The paper also compares the dynamic conditional correlations between developed-emerging markets and between emerging-emerging markets, as follows: (1) between bond markets, the conditional correlations between developed-emerging markets are relatively constant, while the conditional correlations between emerging-emerging markets are dynamic, that is, 2 of 6 pairs (30%) are dynamic; (2) between stock markets, the conditional correlations between developed-emerging markets are relatively constant, as only 1 of 8 (12.5%) pairsa is dynamic, while the conditional correlations between emerging-emerging markets are more dynamic, namely 3 of 6 pairs (50%); and (3) between bond and stock markets, the conditional correlations between developed-emerging markets are more dynamic, with 3 of 16 (19%) being dynamic, compared with that between emerging-emerging markets, which show dynamic conditional correlations in only 3 of 12 pairs (25%).

6. Concluding Remarks

The paper investigated dynamic conditional correlations in international bond, stock and foreign exchange markets. Two models were estimated, namely the DCC model of Engle (2002) and the GARCC model of McAleer et al. (2008). The DCC model suggested that, on average, the conditional correlations of the overall returns did not change over time.

The GARCC model suggested that 38% of pairs of returns displayed dynamic conditional correlations. The conditional correlations between foreign exchange markets were the most dynamic, followed by the conditional correlations between stock and foreign exchange markets, between bond and foreign exchange markets, between bond and stock markets, between stock markets, and between bond markets.

Comparing the correlations between developed-emerging and emerging-emerging markets, several conclusions can be drawn. The conditional correlations between bond-bond markets and between stock-stock markets were relatively constant across developed-emerging markets, while those between emerging-emerging markets tended to be more dynamic. However, the conditional correlations between stock-bond markets across developed-emerging markets were found to be more dynamic as compared with those between emerging-emerging markets.

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Table 1. Summary of Variable Names

Variables	Index Names	Symbol
Indonesian Bond	INDOGB (10 Years MT)	Indbond
Japanese Bond	JP Total 7-10 Years Govt. Index	Japbond
Malaysian Bond	MGS (10 Years MT)	Malbond
Philippines Bond	RPGB (10 Years MT)	Phibond
Thailand Bond	THAIGB (10 Years MT)	Thabond
US Bond	US Benchmark 10 Year Govt. Index	Usabond
Indonesian Stock	Composite Stock Price Index	Indstock
Japanese Stock	Nikkei 225 Stock Avrg. Price Index	Japstock
Malaysian Stock	Kuala Lumpur Comp. Price Index	Malstock
Philippines Stock	Philippine SE Index	Phistock
Thailand Stock	DJSI Thailand Composite	Thastock
US Stock	S&P 500 Composite Price Index	Usastock
Indonesian Rupiah/US dollar		Usdidr
Japanese Yen/US dollar		Usdjpy
Malaysian Ringgit/US dollar		Usdmyr
Philippines Peso/US dollar		Usdphp
Thailand Baht/US dollar		Usdthb

Source: DataStream and Bloomberg database services.

Table 2. DCC and GARCC Models: Estimates of the Conditional Mean and Variance, and Second and Log Moment Conditions

Return	Mean Equations			Variance Equations			Second Moment	Log Moment
	θ_1	θ_2	θ_3	ω	α	β		
Indbond	0.00	-0.03	0.06	**0.00**	**0.25**	**0.79**	1.040	-0.030
Japbond	0.00	-0.29	0.33	**0.00**	**0.10**	**0.88**	0.983	-0.014
Malbond	**-4.9E-05**	**0.61**	**-0.39**	**0.00**	**0.06**	**0.94**	1.002	-0.004
Phibond	0.00	**0.38**	**-0.31**	**0.00**	**0.15**	**0.81**	0.965	-0.038
Thabond	0.00	**0.47**	-0.22	**0.00**	**0.23**	**0.47**	0.698	-0.252
Usabond	0.00	**-0.93**	**0.94**	0.00	**0.02**	**0.93**	0.943	-0.026
Indstock	**2.1E-03**	-0.05	0.22	**0.00**	**0.13**	**0.77**	0.903	-0.055
Japstock	0.00	**0.85**	**-0.86**	**0.00**	**0.07**	**0.92**	0.991	-0.006
Malstock	0.00	0.31	-0.16	**0.00**	**0.03**	**0.97**	0.993	-0.003
Phistock	0.00	0.10	0.08	**0.00**	**0.09**	**0.85**	0.944	-0.029
Thastock	0.00	**0.96**	**-0.92**	0.00	**0.06**	**0.94**	0.999	-0.003
Usastock	0.00	**0.58**	**-0.65**	0.00	**0.04**	**0.93**	0.969	-0.014
Usdidr	0.00	-0.07	0.07	**0.00**	**0.35**	**0.62**	0.974	-0.079
Usdjpy	0.00	0.09	-0.10	0.00	0.03	**0.93**	0.953	-0.021
Usdmyr	0.00	0.10	**-0.72**	**0.00**	**0.57**	**0.52**	1.090	-0.200
Usdphp	0.00	0.04	-0.17	**0.00**	**0.11**	**0.89**	0.997	-0.008
Usdthb	0.00	**-0.91**	**0.92**	**0.00**	**0.11**	**0.81**	0.924	-0.045

Notes: Entries in **bold** in the mean and variance equations are significant at the 5% level.

Table 3. DCC Estimates of the Q_t Model

Parameter estimates	Q_t equation
ϕ_1	0.000004
	(0.001441)
ϕ_2	-0.000557
	(-0.002824)

Note: The two entries for each parameter are their respective estimate and *t*-ratio.

Table 4: GARCC: Estimates of the Q_t Model

No	Pairs of Assets	ϕ_1	ϕ_2	No	Pairs of Assets	ϕ_1	ϕ_2
1	Indbond - Japbond	0.001	-0.083	69	Thabond - Thastock	-0.026	0.083
2	Indbond - Malbond	0.026	0.048	70	Thabond - Usastock	0.006	0.609
3	Indbond - Phibond	0.001	0.308	71	Usabond - Indstock	0.040	-0.138
4	Indbond - Thabond	-0.030	**0.895**	72	Usabond - Japstock	0.029	**0.838**
5	Indbond - Usabond	-0.039	0.385	73	Usabond - Malstock	0.012	**0.990**
6	Japbond - Malbond	-0.032	0.105	74	Usabond - Phistock	0.023	**0.822**
7	Japbond - Phibond	0.015	0.223	75	Usabond - Thastock	-0.030	-0.023
8	Japbond - Thabond	0.011	0.183	76	Usabond - Usastock	0.030	**0.718**
9	Japbond - Usabond	-0.010	0.176	77	Indbond – Usdidr	-0.012	**-0.471**
10	Malbond - Phibond	**-0.027**	**0.948**	78	Indbond – Usdjpy	-0.037	0.039
11	Malbond - Thabond	0.054	0.335	79	Indbond – Usdmyr	-0.052	-0.045
12	Malbond - Usabond	0.059	0.073	80	Indbond – Usdphp	0.047	-0.602
13	Phibond - Thabond	0.005	-0.485	81	Indbond – Usdthb	0.018	0.091
14	Phibond - Usabond	0.036	-0.171	82	Japbond – Usdidr	0.026	0.071
15	Thabond - Usabond	0.045	-0.386	83	Japbond – Usdjpy	0.017	0.021
16	Indstock - Japstock	0.044	-0.047	84	Japbond – Usdmyr	**0.042**	**0.969**
17	Indstock - Malstock	0.022	-0.175	85	Japbond – Usdphp	-0.051	0.293
18	Indstock - Phistock	-0.039	-0.138	86	Japbond – Usdthb	**-0.070**	**-0.754**
19	Indstock - Thastock	**0.043**	**-0.863**	87	Malbond – Usdidr	-0.051	-0.615
20	Indstock - Usastock	0.055	-0.168	88	Malbond – Usdjpy	0.040	-0.169
21	Japstock - Malstock	-0.048	-0.224	89	Malbond - Usdmyr	0.017	0.581
22	Japstock - Phistock	-0.025	-0.030	90	Malbond - Usdphp	0.014	**-0.924**
23	Japstock - Thastock	-0.008	0.174	91	Malbond – Usdthb	-0.016	**-0.832**
24	Japstock - Usastock	0.018	**-0.563**	92	Phibond – Usdidr	0.013	**0.982**
25	Malstock - Phistock	**0.087**	0.287	93	Phibond – Usdjpy	0.010	0.001
26	Malstock - Thastock	-0.012	0.128	94	Phibond – Usdmyr	-0.040	0.637
27	Malstock - Usastock	-0.013	-0.515	95	Phibond – Usdphp	0.001	0.671
28	Phistock - Thastock	-0.026	**-0.772**	96	Phibond – Usdthb	0.007	**-0.828**
29	Phistock - Usastock	0.026	**-0.830**	97	Thabond – Usdidr	0.034	0.614
30	Thastock - Usastock	0.023	0.038	98	Thabond – Usdjpy	**0.075**	0.060
31	Usdidr - Usdjpy	-0.045	**-0.770**	99	Thabond - Usdmyr	-0.028	-0.551
32	Usdidr - Usdmyr	**0.025**	**-0.971**	100	Thabond – Usdphp	-0.020	**-0.971**
33	Usdidr - Usdphp	**0.098**	**0.540**	101	Thabond – Usdthb	-0.037	**-0.733**
34	Usdidr - Usdthb	-0.039	-0.619	102	Usabond – Usdidr	-0.030	**-0.778**
35	Usdjpy - Usdmyr	0.051	**0.632**	103	Usabond – Usdjpy	0.010	0.284
36	Usdjpy - Usdphp	-0.050	-0.244	104	Usabond - Usdmyr	0.045	**0.853**
37	Usdjpy - Usdthb	0.002	-0.941	105	Usabond - Usdphp	-0.018	0.577
38	Usdmyr - Usdphp	0.014	**-0.972**	106	Usabond – Usdthb	0.016	-0.601
39	Usdmyr - Usdthb	-0.011	0.305	107	Indstock – Usdidr	-0.065	0.227
40	Usdphp - Usdthb	0.015	**-0.757**	108	Indstock – Usdjpy	**0.088**	-0.060
41	Indbond - Indstock	-0.002	0.083	109	Indstock - Usdmyr	0.012	**-0.971**
42	Indbond - Japstock	-0.008	-0.152	110	Indstock – Usdphp	0.016	**-0.961**
43	Indbond - Malstock	-0.018	**-0.985**	111	Indstock – Usdthb	0.015	0.222
44	Indbond - Phistock	-0.030	0.227	112	Japstock – Usdidr	0.048	-0.249
45	Indbond - Thastock	0.021	-0.159	113	Japstock – Usdjpy	**0.083**	0.031

46	Indbond - Usastock	0.016	-0.329	114	Japstock - Usdmyr	-0.040	**0.666**
47	Japbond - Indstock	0.034	0.138	115	Japstock – Usdphp	0.023	**-0.933**
48	Japbond - Japstock	0.020	0.257	116	Japstock – Usdthb	0.044	**0.810**
49	Japbond - Malstock	-0.026	-0.379	117	Malstock – Usdidr	-0.053	0.379
50	Japbond - Phistock	-0.018	0.663	118	Malstock – Usdjpy	0.002	0.040
51	Japbond - Thastock	-0.040	-0.429	119	Malstock - Usdmyr	-0.014	-0.793
52	Japbond - Usastock	-0.013	-0.389	120	Malstock - Usdphp	-0.084	**-0.775**
53	Malbond - Indstock	0.023	0.454	121	Malstock – Usdthb	-0.059	-0.489
54	Malbond - Japstock	0.032	0.269	122	Phistock – Usdidr	0.023	-0.746
55	Malbond - Malstock	**0.070**	-0.035	123	Phistock – Usdjpy	0.013	0.755
56	Malbond - Phistock	0.009	-0.027	124	Phistock - Usdmyr	-0.015	**0.809**
57	Malbond - Thastock	0.032	**0.787**	125	Phistock – Usdphp	0.029	-0.676
58	Malbond - Usastock	**0.072**	0.004	126	Phistock – Usdthb	0.033	-0.619
59	Phibond - Indstock	-0.020	0.133	127	Thastock – Usdidr	-0.037	-0.075
60	Phibond - Japstock	-0.024	0.123	128	Thastock – Usdjpy	0.030	**-0.828**
61	Phibond - Malstock	-0.005	**0.968**	129	Thastock - Usdmyr	-0.046	0.583
62	Phibond - Phistock	**-0.070**	0.080	130	Thastock - Usdphp	**0.036**	**0.910**
63	Phibond - Thastock	0.026	-0.355	131	Thastock – Usdthb	-0.045	0.209
64	Phibond - Usastock	-0.020	**0.527**	132	Usastock – Usdidr	0.001	**0.997**
65	Thabond - Indstock	-0.057	0.046	133	Usastock – Usdjpy	0.035	**-0.411**
66	Thabond - Japstock	0.008	0.438	134	Usastock - Usdmyr	-0.016	0.789
67	Thabond - Malstock	0.006	0.593	135	Usastock - Usdphp	**-0.030**	**-0.959**
68	Thabond - Phistock	-0.047	0.260	136	Usastock – Usdthb	0.021	**-0.789**

Note: Entries in **bold** are significant at the 5% level.