The change in relationship between the Asia-Pacific equity markets after the 1997 Financial Crisis

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Abstract

This paper shows that the correlation between a number of markets in the Asia-Pacific region has changed after the Asian financial crisis of 1997. The Dynamic Conditional Correlation (DCC) and a Bivariate Conditional Correlation models are used to estimate the 36 pairwise pre- and post-crisis correlation series for the nine Asia Pacific markets used in this paper. Post-crisis correlation significantly increased for 26 pairwise markets and significantly decreased for 6 pairwise markets. Korea and Japan's relationship with the rest of the markets seem to have substantial changed after the Asian financial crisis. This shift in the relationship between markets will have significant impact on the benefits of diversification in this region.

JEL classification: G15, G14

Keywords: Finance Crisis; Conditional correlation; Asia-Pacific markets

1 Introduction

Several studies have examined the comovement between the Asia-Pacific markets and the markets of the United States, the United Kingdom and Europe. When markets become more correlated, the economic gains from international portfolio diversification diminishes. It is, therefore, important for any investor to understand the nature and the strength of the relationship between markets. This relationship is not a constant one. It changes through time, especially when major world events reshape the relationships. The Asian financial crisis in 1997 had a major impact on most of the Asia-Pacific equity markets. This paper examines the change in the relationship between markets after this crisis. A change in the relationship will affect nature of the benefits from diversification that can be derived from these markets.

2 Literature

When the correlation between markets increase, the benefits from diversifying within the markets declines. Numerous studies have attempted to analyse financial integration between equity markets. The results of these studies are mixed. The studies done on the Asia-Pacific equity markets are not readily comparable, as the markets and the sample periods vary (see Masih and Masih 1997, Roca, Selvanathan and Shepherd 1998, Eun and Resnick 1988, Gosh, Saidi and Johnson 1999).

Phylaktis (1999) finds evidence to support extensive capital market integration in the Pacific Basin region while Bekaert and Harvey (1995) find similar result for stock markets. However, Forbes and Rigobon (2002) find no evidence of significant increase in the financial integration of the markets in this region after the 1997 Asian financial crisis. Although Cappiello, Engle and Sheppard (2003) report that equity returns of the Americas have registered an increase in correlation in the late 90s, they find that the correlation within the Australasian markets have remained unchanged during the late 90s. The Australasian equity markets used in their study include Australia, Hong Kong, Japan and Singapore.

3 Data

This paper uses daily stock market index data from 01/06/1992 to 31/12/2003. The national equity market indices for Australia (All Ordinaries), Hong Kong (Hang Seng), Japan (NIKKEI 225), Korea (SE Composite), Singapore (Singapore Straits Times) and Thailand (Bangkok S.E.T.) were used.

This paper uses daily stock market index data from 01/06/1992 to 31/12/2003. The following national equity market indices were used:

- Australia - ASX - All Ordinaries
- Hong Kong - HS - Hang Seng
- Indonesia - JSE - Jakarta SE Composite
- Japan - NK - NIKKEI 225 Stock Average
- Korea - KSE - Korea SE Composite
- Malaysia - KLC - Kuala Lumpur Composite
- Philippines - PSE - Philippines SE Composite
- Singapore - STI - Singapore Straits Times (New)
- Thailand - BSE - Bangkok S.E.T.

These are the major markets of the Asia-Pacific region and make up almost 15% of the total world market capitalisation. All the reporting for the markets is done alphabetically. The number of observations per series is 3,024 and the total number of observations is 27,216. The data were obtained from Datastream.

4 Methodology

The assumption that the conditional correlations are constant between assets is not realistic in many financial applications. For example Tsui and Yu (1999) found that for certain assets, the assumption of constant correlation does not hold.

Using a multivariate GARCH framework, Engle (2002) relaxes the assumption of constant correlations by allowing the correlations to be time varying. The dynamic conditional correlation multivariate GARCH (DCC-MGARCH) proposed by Engle allows for the correlation component to assume a GARCH type specification. This formulation is similar to the time-varying correlations multivariate GARCH (VC-MGARCH) model proposed by Tse and Tsui (2002), which differs in the scaling used. This paper uses a nine-market DCC-MGARCH and a bivariate conditional correlation models to estimate the time varying correlation between the nine markets.

Engle's (2002) DCC(1,1)-MGARCH model is a convenient way of estimating the correlation using a multivariate approach which results in a reduction in the number of parameters being estimated. However, the model estimates only two parameters for the dynamic conditional correlation. Hence, the 36 series of pair-wise correlations are based on the dynamics of the two parameters estimated. It is valid to question whether the dynamics in the correlation should be the same between every pair of markets.

By allowing each pair-wise market to have its own parameters that enables it to describe its own correlation process, a more realistic estimation of correlation can be achieved. The bivariate conditional correlation model achieves this. For each pair-wise market, a distinctive set of parameters that describe the correlation dynamics is estimated.

The returns for the individual series are calculated based on the logged difference as below:

$$R_{i,t} = 100[ln(P_{i,t}) - ln(P_{i,t-1})] \tag{1}$$

where $P_{i,t}$ is the index of the ith country. The returns are multiplied by 100 for ease of computation. In the GARCH estimation process, the convergence of the algorithms is sensitive to near zero values due to internal rounding off in most of the statistical software programs used. For example, the parameters for the GARCH(1,1) for the returns of Australia are significantly different if the series is not multiplied by 100 when using the MATLAB statistical software.

Instead of using an autoregressive or moving average filtering process, the returns are made mean zero based on a simple demeaning using the unconditional mean of the return series. As Engle and Sheppard (2001) explain, a simple demeaning process should be sufficient since we are interested in modelling the higher moments of the series. Moreover, as we have assumed normal likelihood, the cross partial derivative of the log-likelihood with respect to the mean and variance parameters will have an expectation of zero (Engle and Sheppard 2001). In the estimation process and the simulation process, it would also be computationally convenient to work with fewer parameters.

The zero mean return series, ε_{it} , is calculated for Australia, Hong Kong, Indonesia, Japan, Korea, Malaysia, the Philippines, Singapore and Thailand.

In the multivariate GARCH formulation, the zero-mean return vector $S_t = (\varepsilon_{1t}, \varepsilon_{2t}, \varepsilon_{3t}, ..., \varepsilon_{9t})$ is set to depend on the information set $\Im_{t-1}$ with a variance H_t.

We can express the general form of the multivariate GARCH as:

$$S_t|\Im_{t-1} \sim N(0, H_t) \tag{2}$$

where H_t is a k by k covariance matrix and k is the number of series. As with the univariate case, the main issue is in determining the form that H_t should take. In the univariate case, the unconditional disturbance can be expressed as:

$$\varepsilon_t = \eta_t \sqrt{h_t} \tag{3}$$

where $\eta_t \sim niid$ and the conditional variance, h_t, can be specified to follow the GARCH(p,q) process (Bollerslev 1986) such that:

$$h_t = \omega_0 + \alpha_1 \varepsilon_{t-1}^2 + \ldots + \alpha_q \varepsilon_{t-q}^2 + \beta_1 h_{t-1} + \ldots + \beta_p h_{t-p} \tag{4}$$

where $\omega_0 > 0, \alpha_i \geq 0$, for $i = 1, \ldots, q, \beta_i \geq 0$ for $i = 1, \ldots, p$ are inequality restrictions imposed to ensure that the conditional variance is strictly positive. A summary expression for the above is:

$$h_t = \omega_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i h_{t-i} \tag{5}$$

The estimation of the multivariate models in this paper involves a two-stage estimation process. The first stage is the estimation of the univariate GARCH model for each series. The second stage is the estimation of the dynamic conditional correlations. The estimation will be discussed in the latter part of this paper.

This paper uses the GARCH(1,1) process for modelling the univariate variances. In most time series analyses, a GARCH(1,1) adequately explains the dynamics in the second order of the time series sequence. Diagnostic testing shows that higher order GARCH specifications are not necessary for the data used. Moreover, the moment structure for the GARCH(1,1) is clearly established (see He and Teräsvirta 1999, Karanasos 1999). The GARCH(1,1) model is formulated as:

$$h_t = \omega_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} \tag{6}$$

where $\omega_0 > 0, \alpha_1 \geq 0, \beta_1 \geq 0$.

In the DCC-MGARCH model, the conditional variance is:

$$H_t \equiv D_t R_t D_t \tag{7}$$

where R_t is the time varying correlation matrix and D_t is estimated from the univariate GARCH model. The difference between the specification of H_t in this model and that of Bollerslev (1990) is that the correlation, R_t is allowed to vary with time so that the dynamic nature of the correlation can be captured.

This paper uses a nine-market DCC(1,1)-MVGARCH(1,1) specification. Higher order DCC(1,2) and DCC(2,2) specifications are also estimated for model comparison. However, model comparison using the likelihood ratio test, the Akaike information criterion (AIC) and the Bayesian information criterion (BIC) show that the DCC(1,1) specification, adequately captures the dynamics of the correlation process.

For the nine-market DCC-MGARCH model, the elements of the matrix D_t will take the form:

$$D_t = \begin{bmatrix} \sqrt{h_{11,t}} & 0 & \cdots & 0 \\ 0 & \sqrt{h_{22,t}} & \cdots & 0 \\ 0 & 0 & \ddots & \vdots \\ 0 & 0 & \dots & \sqrt{h_{99,t}} \end{bmatrix} \tag{8}$$

The DCC-MGARCH uses a two-stage estimation procedure. The first stage is the conventional univariate GARCH parameter estimation for each zero mean series. The residuals from the first stage are then standardised and used in the estimation of the correlation parameters in the second stage.

The correlation structure is given as:

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1} \tag{9}$$

The covariance structure for a DCC(1,1) is specified by a GARCH type process as below:

$$Q_t = (1 - \lambda_1 - \mu_1)\overline{Q} + \lambda_1(\eta_{t-1}\eta'_{t-1}) + \mu_1 Q_{t-1} \tag{10}$$

where the covariance matrix, Q_t, is calculated as a weighted average of $\overline{Q}$, the unconditional covariance of the standardised residuals; $\eta_{t-1}\eta'_{t-1}$, a lagged function of the standardised residuals; and Q_{t-1}, the past realisation of the conditional covariance. In the DCC(1,1) specification only the first lagged realisation of the covariance of the standardised residuals and the conditional covariance are used. This requires the estimation of two additional parameters, λ_1 and μ_1. Q^* is a diagonal matrix whose elements are the square root of the diagonal elements of Q_t. Hence, for a nine-market specification it would take the form:

$$D_t = \begin{bmatrix} \sqrt{q_{11,t}} & 0 & \cdots & 0 \\ 0 & \sqrt{q_{22,t}} & \cdots & 0 \\ 0 & 0 & \ddots & \vdots \\ 0 & 0 & \dots & \sqrt{q_{99,t}} \end{bmatrix} \tag{11}$$

The off diagonal elements in the matrix R_t will be $\rho_{12,t} = q_{12,t}/\sqrt{q_{11,t}q_{22,t}}$, where $\rho_{12,t}$ is the conditional correlation between market 1 and market 2. The constant correlation multivariate GARCH is nested within this model. If $\lambda_1 = \mu_1 = 0$ and $\overline{q_{11,t}} = 1$, the constant correlation model is obtained. Thus, the constant correlation hypothesis can be tested in this framework.

It follows that if $\overline{Q}$ and $\eta_{t-1}\eta'_{t-1}$ are positive definite and diagonal, Q_t then will also be positive definite and diagonal. For the DCC to be positive definite, both the univariate GARCH parameter restriction and the DCC parameter restrictions must be satisfied for all series. As the moment conditions for the GARCH(1,1) have already been discussed earlier, it would be useful to discuss restriction for the DCC parameters. Engle and Sheppard (2001) prove that the following sufficient conditions must be satisfied for the DCC parameters to ensure the positive definiteness of H_t:

It is more convenient to estimate the DCC model using a two-stage estimation procedure. Engle (2002) split the model into two parts - the univariate variances and the correlations. Although the two-stage estimation is inefficient, it is still consistent. Engle and Sheppard (2001) provide a scrutable exposition of the proofs for consistency and asymptotic normality of the parameter estimates.

If we let θ be parameters of the model comprising first stage GARCH variance parameters, ϕ, and the second stage correlation parameters, ψ, we can express the first stage quasi-likelihood function as:

$$
\begin{aligned}
QL_1(\phi|\varepsilon_t) &= -\frac{1}{2}+\sum_{t=1}^{T}(k\log(2\pi)+\log|I_k|+2\log|D_t|+\varepsilon_t' D_t^{-1} I_k D_t^{-1}\varepsilon_t) \\
&= -\frac{1}{2}+\sum_{t=1}^{T}(k\log(2\pi)+2\log|D_t|+\varepsilon_t' D_t^{-2}\varepsilon_t) \\
&= -\frac{1}{2}\sum_{t=1}^{T}\left(k\log(2\pi)+\sum_{n=1}^{k}(\log h_{it}+\frac{\varepsilon_{it}^2}{h_{it}})\right) \\
&= -\frac{1}{2}\sum_{n=1}^{k}\left(T\log(2\pi)+\sum_{t=1}^{T}(\log h_{it}+\frac{\varepsilon_{it}^2}{h_{it}})\right) \qquad (12)
\end{aligned}
$$

where I_k is an identity matrix of size k. The above log-likelihood function is the same as that for the univariate GARCH estimation. Although a t-distribution or a General Error distribution can be used, for convenience, the variance parameters in the first stage are usually estimated assuming normal distribution in the disturbance terms. The assumption of Gaussian innovations is used in this paper. The parameters estimated in the first stage are used to condition the likelihood for the second stage estimation.

$$
\begin{aligned}
QL_2(\psi|\hat{\phi},r_t) &= -\frac{1}{2}+\sum_{t=1}^{T}(k\log(2\pi)+2\log|D_t|+\log|R_t|+\varepsilon_t' D_t^{-1}R_t^{-1}D_t^{-1}\varepsilon_t) \\
&= -\frac{1}{2}+\sum_{t=1}^{T}(k\log(2\pi)+2\log|D_t|+\log|R_t|+\eta_t' R_t^{-1}\eta_t) \qquad (13)
\end{aligned}
$$

The DCC parameters, in ψ, are conditioned on the estimated value of the variance parameters, in $\hat{\phi}$, and η_t is the standardised residual derived from the first stage univariate GARCH estimation, which is assumed to be *n.i.d.* with a mean zero and a variance, R_t. That is, $\eta_t = \varepsilon_t/\sqrt{h_t}$ for the individual series. Hence, the variance matrix, R_t, is also the correlation matrix of the original zero mean return series. In the actual estimation process, the constant term is omitted as it does not influence the parameters. Hence, for the estimation of the above equation is simplified to:

$$QL_2^*(\psi|\hat{\phi}, r_t) \quad = \quad -\frac{1}{2} + \sum_{t=1}^{T} (\log |R_t| + \eta_t' R_t^{-1} \eta_t) \tag{14}$$

The correlations estimated must lie between -1 and 1. Hence, there must be a rescaling process that must be used to make sure that the estimates of correlations are within these bounds. Looking at the DCC model, the covariance is estimated using a GARCH-like process. This covariance is then scaled by the diagonal matrix of the standard deviations. Under Cauchy-Schwartz inequality, R_t behaves like a standard correlation matrix.

The bivariate conditional correlation model is based on the DCC framework with parsimonious parameter specification for the GARCH variance process and the dynamic correlation process. A GARCH(1,1) specification is used for the variance parameters and a DCC(1,1) is used for the correlation component. The variance is governed by:

$$h_t = \omega + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1} \tag{15}$$

where $\omega > 0, \alpha \geq 0, \beta \geq 0$. The pair-wise correlation will be estimated as:

$$\rho_{12,t} = \frac{(1-\lambda-\mu)\overline{q}_{12} + \lambda(\eta_{1,t-1}\eta_{2,t-1}) + \mu q_{12,t-1}}{\sqrt{((1-\lambda-\mu)\overline{q}_{11} + \lambda\eta_{1,t-1}^2 + \mu q_{11,t-1})((1-\lambda-\mu)\overline{q}_{22} + \lambda\eta_{2,t-1}^2 + \mu q_{22,t-1})}} \tag{16}$$

where, the restrictions, $\lambda \geq 0$, $\mu \geq 0$ and $\lambda + \mu < 1$ are imposed to ensure stationarity. The robust standard errors are estimated in the same way as for the multivariate DCC model. A similar two-stage estimation process is used.

Analysis is done on the correlation estimates computed from the DCC(1,1) MGARCH and the bivariate conditional correlation models. The data is divided into two distinct periods. The pre-1997 period dates from June 01, 1992 to July 01, 1997 comprising of 1326 observations and the post-1997 period dates from July 01, 1998 to December 31, 2003 comprising of 1436 observations for each series. The period of the crisis between July 02, 1997 to June 31, 1998 was omitted. This was done to give the data a discernable break. The extreme correlations that might have resulted from this period due to the financial crisis are therefore not included.

The null hypothesis of interest is:

$$H_o : \rho_{pre} - \rho_{post} = 0 \tag{17}$$

If the null hypothesis is rejected, then there is a significant difference between the pre- and the post-crash correlations.

5 Results

The parameter estimates of the dynamic conditional correlation of Engle (2002) are reported in Table 1. Three different parameterisations of the DCC model were estimated to facilitate model selection. The DCC(1,1), DCC(1,2) and the DCC(2,2) were estimated to illustrate that a parsimonious DCC(1,1) model is sufficient to capture the dynamics in the conditional correlation. The condition, $\sum_{m=1}^{M} \lambda_m + \sum_{n=1}^{N} \mu_n < 1$, is met for all specifications of the DCC model, ensuring that the process is strictly stationary and ergodic.

The *lamda* is the coefficient for the lagged function of the standardised residuals. The *mu* is the coefficient for the past realisation of the conditional covariance. The two coefficients work in the same way as in an ARMA type specification. In most cases, one lag in the function of the standardised residual and the past realisation of conditional covariance is sufficient to capture the dynamics of the process. Table 1 clearly confirms this observation. The parameter estimates for

Table 1: Parameter estimates for the DCC-MGARCH models.

	DCC Parameters				
	λ_1	λ_2	μ_1	μ_2	sum of parameters
DCC(1,1)	0.0096 (0.0034)		0.9794 (0.0110)		0.9889
Log-likelihood	-42987.0121				
DCC(1,2)	0.0143 (0.0040)		0.4300 (0.1309)	0.5398 (0.1363)	0.9840
Log-likelihood	-42981.2769				
DCC(2,2)	0.0143* (0.0069)	0.0000* (0.0131)	0.4298* (0.7715)	0.5399* (0.7574)	0.9840
Log-likelihood	-42981.2782				

The parameter estimates of the dynamic conditional correlation model are reported in this table. The robust standard errors are reported in the parentheses.
* insignificant at the 1% level of significance.

the DCC(1,1) specification are significant. The t-statistics from the standardised residuals for λ_1 and μ_1 are 2.82 and 89.15, respectively. These t-statistics strongly reject the insignificance of the parameter estimates at any conventional level of significance. The DCC(1,2) specification has two lags in the past realisation of the conditional covariance. The parameter estimates for μ_1 and μ_2 are almost half the value of the μ_1 in the DCC(1,1). The standard errors are also markedly higher for the DCC(1,2). The t-statistics were 3.61, 3.29 and 3.96 for λ_1, μ_1 and μ_2, respectively, which are significantly smaller compared to that of the DCC(1,1) t-statistics.

The parameter estimates for DCC(2,2) on the other hand were statistically insignificant at the 1% level of significance. The t-statistics were 2.07, 0.00, 0.56 and 0.71 for λ_1, λ_1, μ_1 and μ_2, respectively. Therefore, this specification for the correlation dynamics can be discarded.

Table 2 reports the calculated values of the AIC and the BIC. Both the criteria favour the more parsimonious specification of DCC(1,1). Coupled with the significance of the parameter estimates based on the t-statistics, the DCC(1,1) is a suitable model amongst the family of the DCC models to adequately capture

Table 2: The AIC and BIC criteria for various DCC specifications.

	Information Criteria	
DCC specification	Akaike Information Criteria	Schwarz Information Criteria
DCC(1,1)	-85916.0242*	-85741.6468*
DCC(1,2)	-85902.5538	-85722.1634
DCC(2,2)	-85900.5564	-85714.1530

* The smallest calculated value based on a fixed number of observations.

the dynamics in the conditional correlation.

Table 3 reports the parameter estimates for the correlation component of the bivariate conditional correlation model. The parameter estimates for the GARCH component of the model is the same as that of the DCC model.

For most pair-wise markets, the *lambda* is higher than the *lambda* estimated using the DCC model. Thus, it is easy to observe that the persistence in the correlation for each pair-wise market is different. The lowest *lambda* of 0.6532 is recorded for Japan and Malaysia, and the highest of 0.9951 for Korea and Malaysia.

The standard errors for the estimates are provided in the parentheses. All the *lambda* estimates are significant at the 1% level of significance. The standard errors for *mu* are much higher than that for the *lambda*. Not all the *mu* estimates are significant. The log-likelihood is also provided for each pair-wise estimation.

Table 3: Bi-Variate Conditional Correlation GARCH results.

		Hong Kong	Indonesia	Japan	Korea	Malaysia	Philippines	Singapore	Thailand
Australia	μ	0.0200	0.0238	0.0183	0.0065	0,0086	0.0106	0.0300	0.0082
		(0.0265)	(0.0097)	(0.0066)	(0.0021)	(0.0059)	(0.0058)	(0.0120)	(0.0037)
	λ	0.9515	0.8727	0.9625	0.9935	0.9611	0.9768	0.8944	0.9816
		(0.0987)	(0.0683)	(0.0176)	(0.0023)	(0.0213)	(0.0143)	(0.0389)	(0.0076)
	Loglik	-8699	-8373	-8530	-9339	-8236	8625	-8008	-9031
Hong Kong	μ		0.0469	0.0064	0.0511	0.0249	0.0065	0.00513	0.0253
			(0.0096)	(0.0022)	(0.0243)	(0.0080)	(0.0091)	(0.0090)	(0.0071)
	λ		0.8888	0.9926	0.9489	0.9458	0.9862	0.9105	0.9633
			(0.0231)	(0.0026)	(0.0254)	(0.0239)	(0.0240)	(0.0180)	(0.0118)
	Loglik		-10365	-10566	-11336	-10177	-10658	-9721	-10947
Indonesia	μ			0.0167	0.0198	0.0064	0.0189	0.0357	0.0117
				(0.0128)	(0.0097)	(0.0038)	(0.0106)	(0.0084)	(0.0050)
	λ			0.8761	0.9319	0.9876	0.9720	0.9237	0.9800
				(0.0823)	(0.0266)	(0.0091)	(0.0203)	(0.0206)	(0.0097)
	Loglik			-10179	-10931	-9689	-10073	-9529	-9258
Japan	μ				0.0085	0.0411	0.0129	0.0263	0.0105
					(0.0036)	(0.0199)	(0.0043)	(0.0141)	(0.0041)
	λ				0.9910	0.6532	0.9765	0.9478	0.9828
					(0.0043)	(0.2411)	(0.0096)	(0.0304)	(0.0068)
	Loglik				-11101	-10025	-10434	-9849	-10831
Korea	μ					0.0040	0.0097	0.0065	0.0106
						(0.0025)	(0.0071)	(0.0022)	(0.0104)
	λ					0.9951	0.9821	0.9929	0.9835
						(0.0038)	(0.0170)	(0.0025)	(0.0203)
	Loglik					-10805	-11187	-10580	-11547
Malaysia	μ						0.0115	0.0434	0.0535
							(0.0233)	(0.0203)	(0.0177)
	λ						0.9634	0.9250	0.8565
							(0.1178)	(0.0500)	(0.0706)
	Loglik						-9990	-9242	-10299
Philippines	μ							0.0177	0.0227
								(0.0080)	(0.0072)
	λ							0.9702	0.9620
								(0.0122)	(0.0139)
	Loglik							-9839	-10758
Singapore	μ								0.0232
									(0.0074)
	λ								0.9649
									(0.0135)
	Loglik								-10132

Table 4 reports on the pre- and post-Asian financial crisis results. The pre- and post-crisis correlations are the arithmetic average over the sample periods. The tick indicates that the pre- and post-crisis correlations are significantly different at the 1% level of significance. The asterisk indicates that the post-crisis correlation is lower than the pre-crisis correlation.

For a majority of the markets, the post-crisis correlation is higher than the pre-crisis correlations. However, the correlation decreased after the financial crisis for Hong Kong and Malaysia, Indonesia and Malaysia, Indonesia and the Philippines, Indonesia and Singapore, Malaysia and the Philippines, Malaysia and Singapore, Malaysia and Thailand, and the Philippines and Singapore. The decline in the correlation is significant except for Malaysia and the Philippines correlation. This result is consistent for both the bivariate and the DCC models except for the Philippines and Singapore correlation. It is also interesting to note that this decline is registered in most of the correlations that result from Malaysia and the Philippines markets with other markets in the region.

For those markets that register an increase in post-crisis correlation, the increase is insignificant only for the correlation between Australia and Indonesia, Hong Kong and Indonesia, and the Philippines and Singapore.

There is clear evidence that the correlation has increased for a majority of the markets after the 1997 Asian financial crisis. The biggest increase in correlation is between Japan and Korea. There is also a large increase in the correlation between Australia and Korea, Korea and Singapore, and Hong Kong and Korea.

An interesting finding is that the markets of Japan and Korea have become more correlated with a majority of the other markets in this region. There is a substantial increase in the post-crisis correlations between Australia and Japan, Hong Kong and Japan, Japan and Korea, Japan and the Philippines, Japan and Singapore, and Japan and Thailand. The increase in correlation between Indonesia and Japan, and Japan and Malaysia is small but, nevertheless, significant.

For Korea, its correlation has increased substantially with the markets of Australia, Hong Kong, Japan, Malaysia, the Philippines, Singapore and Thailand.

Another interesting finding is the decline in the correlation between Malaysia and a majority of the markets in the region. There is a substantial decline in

Table 4: Comparison between pre- and post-Asian financial crisis correlation.

	Bivariate			DCC(1,1)		
	Pre	Post	sig	Pre	Post	sig
Australia & Hong Kong	0.3979	0.4434	√	0.3963	0.4485	√
Australia & Indonesia	0.2095	0.2148		0.2014	0.2190	
Australia & Japan	0.2888	0.3842	√	0.2835	0.3832	√
Australia & Korea	0.0756	0.3786	√	0.1577	0.3116	√
Australia & Malaysia	0.2297	0.2368	√	0.2261	0.2408	√
Australia & Philippines	0.2019	0.2290	√	0.2018	0.2292	√
Australia & Singapore	0.3489	0.3809	√	0.3402	0.3924	√
Australia & Thailand	0.2042	0.2397	√	0.2028	0.2399	√
Hong Kong & Indonesia	0.2575	0.2617		0.2582	0.2665	
Hong Kong & Japan	0.2203	0.4425	√	0.2768	0.3997	√
Hong Kong & Korea	0.2795	0.5594	√	0.1845	0.3826	√
Hong Kong & Malaysia	0.3491	0.3158*	√	0.3521	0.3178*	√
Hong Kong & Philippines	0.2252	0.2521	√	0.2249	0.2507	√
Hong Kong & Singapore	0.4748	0.5568	√	0.4934	0.5595	√
Hong Kong & Thailand	0.3153	0.3465	√	0.3251	0.3450	√
Indonesia & Japan	0.1563	0.1684	√	0.1361	0.1799	√
Indonesia & Korea	0.1121	0.1688	√	0.0955	0.1863	√
Indonesia & Malaysia	0.2770	0.2565*	√	0.2765	0.2578*	√
Indonesia & Philippines	0.2581	0.2256*	√	0.2570	0.2346*	√
Indonesia & Singapore	0.3245	0.3078*	√	0.3281	0.3134*	√
Indonesia & Thailand	0.2433	0.2616	√	0.2469	0.2614	√
Japan & Korea	0.0093	0.3895	√	0.1158	0.3135	√
Japan & Malaysia	0.1999	0.2131	√	0.1766	0.2349	√
Japan & Philippines	0.0924	0.1956	√	0.1019	0.1883	√
Japan & Singapore	0.2414	0.3534	√	0.2488	0.3502	√
Japan & Thailand	0.1191	0.2228	√	0.1317	0.2108	√
Korea & Malaysia	0.0724	0.1907	√	0.0980	0.1761	√
Korea & Philippines	0.0794	0.1919	√	0.0883	0.1843	√
Korea & Singapore	0.0920	0.4268	√	0.1790	0.3635	√
Korea & Thailand	0.1984	0.2880	√	0.1613	0.2694	√
Malaysia & Philippines	0.2156	0.2141*		0.2145	0.2120*	
Malaysia & Singapore	0.4791	0.3697*	√	0.4732	0.3875*	√
Malaysia & Thailand	0.3151	0.3048*	√	0.3202	0.3112*	√
Philippines & Singapore	0.2587	0.2601		0.2648	0.2644*	
Philippines & Thailand	0.2052	0.2378	√	0.2132	0.2379	√
Singapore & Thailand	0.3578	0.3821	√	0.3662	0.3817	√

The mean is the arithmetic mean of the daily conditional correlation over the sample period. The pre-1997 correlation is the mean until July 01, 1997 comprising of 1326 observations and the post-1997 correlation are the mean from July 01, 1998 comprising of 1436 observations.
* The post-1997 is lower than the pre-1997 mean. √ significant at 1%.

the correlation between Malaysia and Singapore. The other markets that have become less correlated with Malaysia after the crisis are Hong Kong, Indonesia and Thailand. The pegging of the Malaysian ringgit to the US dollar may have contributed to the decline in the integration of Malaysia with the rest of the markets. There is also a significant decline in the correlation between Indonesia and the markets of the Philippines and Singapore.

6 Conclusions

The result from the analysis of the pre- and post-correlation provides strong evidence of an increase in the correlations between a majority of the markets in this region after the Asian financial crisis. Korea's and Japan's correlations with the other markets in the region seem to have substantially increased. The markets of Korea and Japan seem to register the highest increase in post-crisis correlation. This has serious implications for investors contemplating portfolio diversification in this region.

There is also a significant decline in the correlation between Malaysia and the rest of the region. The pegging of the ringgit can be cited as a plausible reason. The correlation with the Indonesian market has also declined against some of the markets in the region.

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