ESTIMATING THE CORRELATION OF INTERNATIONAL EQUITY MARKETS WITH MULTIVARIATE EXTREME AND GARCH MODELS

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Abstract

In this paper we study the dependence structure of extreme realization of returns between seven Asian Pasific stock markets and the USA. Methodologically, we apply the Multivariate Extreme Value theory that best suits to the problem under investigation. The main advantage of this approach is that it generates dependence measures even if the multivariate Gaussian distribution does not apply, as the case is for the tails of the high frequency stock index returns distributions. The empirical evidence suggests that conventional Constant Conditional Correlation *GARCH* models (Bollerslev, 1990) produce very similar results not just quantitatively but qualitatively so, as a clustering analysis showed. Dynamic Conditional Correlation GARCH models (Engle, 2002) are also estimated which produce substantially different results.

JEL Classification: G15; C10; F30.

Keywords*; Extreme Value Dependence; Multivariate GARCH; Emerging markets.*

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1. **Introduction**

It is empirically documented that in crisis periods the correlation index of emerging equity markets returns tends to rise and this is often invoked as an argument against the diversification benefits of investing in those markets. However, Boyer *et.al.* (1999), among others, argue that from a completely statistical perspective one would expect higher correlations during periods of high volatility and therefore the policy of splitting a dataset into sub-periods of interest can yield misleading results. A valid alternative procedure would be to employ models representative of the data generating process, which build in the possibility of structural changes (e.g. the regime switching models of Ang and Bekaert, 2002). Bekaert, Harvey and Ng (2003) follow a more structural approach that disassociates the notion of contagion from the increased correlation. In this framework contagion is defined as the excess correlation that is not explained by higher factor volatility.

Notwithstanding the difficulties surrounding the estimation of the correlation coefficient over crisis periods, a more critical issue appears to be the suitability of correlation as a dependence measure. This reservation stems from the fact that the Pearson correlation coefficient will represent the dependence measure between two variables only if the dependence structure is Gaussian over the whole distribution. This is however rather unlikely considering the distribution properties of high frequency stock market returns. Recently, a number of studies have implemented asymptotic results from the multivariate extreme value theory (MEVT) in order to estimate the conditional correlation of international equity returns. The attractive feature of the MEVT is that its results hold for a wide range of parametric distributions of returns and not only for the multivariate normal. Longin and Solnik (2001) model the multivariate distribution of positive and negative monthly return exceedances, which are linked to high values of corresponding thresholds, of the five largest stock markets. They conclude that the assumption of multivariate normality cannot be accepted (rejected) for large negative (positive) returns. The estimated correlation coefficients are always higher in the case of return exceedances for negative thresholds and they tend to increase with the absolute size of the threshold. Poon *et. al.* (2004) argue that traditional tests for asymptotic extremal dependence bias the results in favor of this hypothesis and they suggest an additional measure of extremal dependence for variables that are asymptotically independent. They apply the pair of dependence measures on daily data of five stock index returns of the largest stock markets and they conclude that the asymptotic dependence between the European countries (United Kingdom. Germany and France) has increased over time but that the asymptotic independence between Europe, United States and Japan best characterizes their stock markets behavior.

In this paper we apply the MEVT in order to estimate the dependence structure of extreme realizations of equity returns between mature (USA, Japan) and emerging Asian stock markets (Hong Kong, Taiwan, Malaysia, Indonesia, Singapore and Thailand). The results are compared to those obtained from two classes of MGARCH models: the constant conditional correlation (CCC) model proposed by Bollerslev (1990) and the dynamic conditional correlation (DCC) model by Engle (2002).

The above testing methodology for the dependence structure stands in stark contrast to classical multivariate analysis which is performed jointly for the marginal distributions and the dependence structure by considering the complete covariance matrix (e.g. MGARCH models). So in the so-called copula approach we analyze separately the main diagonal elements (scatter measures) of the covariance matrix from the dependence structure contained in the off-diagonal elements that are "not contaminated" by the scatter parameters.

In the next section we offer a brief presentation of the copula methodology that allows the extraction of the dependence structure of a set of variables independently of the marginal distributions, which might refer to a wide class of models. Then the MEVT and the MGARCH approaches are applied on a rather popular in the relevant literature data set that comprises of daily stock market returns of most of the Far East Asian emerging capital markets. Moreover, we have also included the S&P 500 as well as the NiKkei 225 indices. Dependence measures are estimated for all possible pairs of series and the results are discussed in the third part of the paper. The main evidence is that the dependence measures from the MEVT for negative returns (long positions) are marginally higher than those obtained from MGARCH models. In order to facilitate the classification of the pairs of countries into different zones of dependence we have applied a clustering analysis that shows that the different estimation techniques are not critical if one wishes to classify each stock market according to its degree of dependence on the other markets.

2. **Parametric estimation of the dependence structure of multivariate extremes**

Copulas, or dependence functions, represent a way of trying to extract the dependence structure from the joint distribution. This is being accomplished by separating the joint distribution into a part that describes the dependence structure and a part that describes the marginal behavior only. Let us consider a q-dimensional vector of random returns denoted by $Y^t = (Y_1, Y_2, ... Y_q)^t$ with marginal distributions $F_1, ..., F_q$. The joint distribution function C of $(F_1(Y_1), ... F_q(Y_q))^t$ is then called the copula of the random vector $Y^t = (Y_1, Y_2, ... Y_q)^t$. It follows then that:

$$F(y^*{}_1, ... y^*{}_q) = \Pr ob[Y_1 \leq y^*{}_1, ..., Y_q \leq y^*{}_q] = C(F_1(y^*{}_1), ..., F_q(y^*{}_q)), \qquad (1)$$

where $y^*{}_i = u_i + y_i$ and y_i refers to the exceedance of Y_i over the threshold u_i.

Once the problem is to study the dependence structure of extreme returns, the multivariate return exceedances distribution must be defined. As with the univariate case the exact distribution is not exactly known and therefore we have to consider asymptotic results. The possible limit non-degenerate distribution however must satisfy two properties; first, the fat-tails feature of univariate returns and second the empirical regularity that correlations rise at crisis periods. The first property is satisfied by the Generalized Pareto Distribution (*GPD*) function that is given by

$$\begin{aligned}G(y) &= 1-\{1+\xi y/\sigma\}^{-1/\xi}, \xi \neq 0 \\ G(y) &= 1-\exp(-y), \xi = 0\end{aligned}, \qquad (2)$$

where ξ is the tail index, $\sigma > 0$ the scale parameter and the support is $y \geq 0$ when $\xi > 0$ and $0 < y < -(\sigma/\xi)$ when $\xi < 0$. Essentially all the common continuous distributions of statistics belong in this class of distributions. For example the case $\xi > 0$ corresponds to heavy tailed distributions such as the Pareto and Student-*t*. The case $\xi = 0$ corresponds to distributions like the normal or the lognormal whose tails decay exponentially. The short-tailed distributions with a finite endpoint such as the uniform or beta correspond to the case $\xi < 0$.

The second property is satisfied by the logistic model in the bivariate extreme value family that is given by:

$$C(s,t) = \Pr(S \leq s, T \leq t) = \exp\left[-\left\{s^{-(1/a)} + t^{-(1/a)}\right\}^{a}\right], 0 < a \leq 1, \qquad (3)$$

(Poon *et. al.* (2004), Longin and Solnik (2001)). In order to disassociate the correlation structure from the marginal distributions the bivariate return exceedances have been transformed to unit Fréchet margins

$$S = -1/\log F_{u_1}(y_1), \quad T = -1/\log F_{u_u}(y_2)$$

where $F_{u_i}(y_i)$ is the *GPD* of exceedance y_i. The asymptotic dependence of *(S,T)* is defined by:

$$\chi = \lim_{s \to \infty} \Pr(T \succ s / S \succ s), \qquad (3)$$

where $0 \leq \chi \leq 1$, and the two variables are termed asymptotically dependent if $\chi \geq 0$ and asymptotically independent if $\chi = 0$. The relationship between the coefficient α, of eq. (3), and χ is given by $\chi = 2 - 2^{\alpha}$ so when the variables are exactly independent $\chi = 0$ and $\alpha = 1$ while when $\alpha \prec 1$ the variables are asymptotically dependent to a degree depending on α.

Once we have chosen the thresholds, the bivariate distribution of return exceedances is described by seven parameters: the two tail probabilities, the dispersion parameters, the tail indexes of each variable, and the dependence parameter of the logistic function. The parameters of the model are estimated by the maximum likelihood method. In the bivariate case, the correlation coefficient of extremes is related to the coefficient of dependence by (Tiago de Oliveira, 1973; Longin and Solnik, 2001):

$$\rho = 1 - \alpha^2 . \qquad (4)$$

In order to investigate the empirical implications of those two different testing philosophies we have also chosen to estimate the correlation indices from multivariate volatility models. The first model we estimate is the one suggested by Bollerslev (1990) that handles the high dimensionality of the parameter space of the variance – covariance matrix by adopting the assumption of constant contemporaneous correlations (CCC). In the CCC GARCH specification the conditional variance matrix is specified as $H_t \equiv D_t R D_t$, where H $_t$ takes the form:

$$H_t = \begin{bmatrix} \sqrt{h_{11,t}} & 0 \\ 0 & \sqrt{h_{22,t}} \end{bmatrix} \begin{bmatrix} 1 & \rho_{12} \\ \rho_{21} & 1 \end{bmatrix} \begin{bmatrix} \sqrt{h_{11,t}} & 0 \\ 0 & \sqrt{h_{22,t}} \end{bmatrix} . \qquad (5)$$

For the bivariate GARCH(1,1) case the CCC model contains only 7 parameters compared to 21 encountered in the full model and the positive definiteness of the variance – covariance matrix is easily satisfied ($|\rho| < 1$). In this framework the asymmetric behavior of the conditional covariances in bull and bear markets is guaranteed by the proper parameterization of the conditional variances.

The assumption that the conditional correlations are constant may seem unrealistic in many empirical applications like the dependence of international equity returns. Engle (2002) extends the CCC estimator by allowing the conditional correlations to be time varying, that is the conditional variance is $H_t \equiv D_t R D_t$. The dynamic conditional estimator (DCC) is obtained in two stages. In the first stage the univariate GARCH models are estimated for each return series. The standardized residuals from the first stage, $n_t = (Y_\tau^* / \sqrt{h_t})$, which are assumed to be *n.i.d.* with a mean zero (Y^*) and a variance $R_{t,}$, are used in the second stage in the estimation of the correlation parameters. The correlation structure R is also the correlation of the original data and is given by $R_t = Q_t^{*-1} Q_t Q_t^{*-1}$, where the covariance matrix Q is specified by a GARCH process as below:

$$Q_t = S(1-\alpha-\beta) + \alpha(n_{t-1}n_{t-1}^{'}) + \beta Q_{t-1}. \qquad (6)$$

Q the unconditional covariance matrix is calculated as a weighted average of S the unconditional covariance of the standardized residuals, a lagged function of the standardized residuals and the past realization of the conditional variance. Q^* is a diagonal matrix whose elements are the square root of the diagonal elements of Q (Engle, 2002).

3. Empirical evidence

We have applied the 3 competing models on a data set consisting of daily returns of the following equity indices: S&P 500 Composite (USA), Nikkei 255 Stock Average (Japan), Hang Seng Price Index (Hong Kong), the Stock Exchange Weighted Price Index of Taiwan, KLCI Composite Price Index (Malaysia), the Jakarta Stock Exchange Composite Price Index (Indonesia), the Straits Times (New) Price Index (Singapore), The SET 100 Basic Industries Index (Thailand). The data cover the period 5/1/87 – 31/12/04. Estimates of the dependence coefficient have been obtained over two subperiods, 5/1/87-5/3/01 and 2/11/90 – 31/12/04, with the purpose to check the sensitivity of our estimates on the inclusion or not of the turbulent period surrounding the October 1987 stock exchange crisis.

The MEVT is applied on the exceedances of the return series from high enough, positive or negative, thresholds *(Peak over Threshold, POT, method)*. The choice of the threshold is of critical importance and various methods have been proposed that range from visual inspection of the mean excess function to bootstrapping techniques (Danielsson and deVries, 1997). In order to estimate the threshold, u, for the *POT* method we follow Neftci

(2000) according to whom $u = 1.176\sigma_n$. σ_n is the standard deviation of $(Y_t)_{t=1}^{n}$ and $1.176 = F_t^{-1}(0.10) = 1.44\sqrt{(\nu-2)/\nu}$ when a Student-*t* *(ν=6)* distribution, F, is being assumed that is the excesses over the threshold belong to the 10% tails.

In table 1 we present the estimates of the tail index of equation (2), *ξ,* for the individual time series. The evidence suggests that we cannot reject the Gaussian distribution for the stock index returns of Japan and Taiwan while the same applies for the USA index when the October 1987 crisis is excluded. For the remaining Far East Asian markets the existence of fat tails for both positive and negative excess returns cannot be excluded. In table (2) we present the correlation coefficients from the *MEVT* and the two *GARCH* models. In both the *CCC* and the *DCC* models we allow for asymmetric behavior of the univariate GARCH processes by incorporating the Glosten *et. al.* (1993) GARCH model. We conclude that the estimated extreme correlation coefficients of negative returns (long positions) are always higher than those for the extreme positive returns. The estimates of the extreme correlations of negative returns are higher than those obtained from the multivariate GARCH models and the unconditional estimate, although the differences are rather marginal.

In order to classify the various pairs of capital markets into different groups according to the estimated dependence measures, we apply a clustering analysis that assigns each estimate to the cluster having the nearest mean. K-means is one of the simplest unsupervised learning algorithms that solve the well known clustering problem. The procedure follows a simple and easy way to classify a given data set through a certain number of clusters (assume k clusters) fixed a priori. The main idea is to define k centroids, one for each cluster. Group membership is determined by calculating the centroid for each group (*the multidimensional version of the mean*) and assigning each observation to the group with the closest centroid, (MacQueen, 1967). The evidence appears in table 3. The main result is that the classification of the estimated correlations into low, medium and high dependence groups is very similar between the *MEVT* and the *CCC* estimates independently of the estimation period. The *DCC* correlation estimates are more sensitive, as expected, to the last observation included in the sample and this accounts for the different classification of the pairs of countries that is produced. Finally, the classification of the correlation coefficients of extreme positive returns and those of extreme negative returns are very similar.

4. **Concluding remarks**

In this paper we studied the dependence structure of extreme realization of returns between seven Far East Asian stock markets and the USA. Methodologically, we applied the Multivariate Extreme Value theory that best suits to the problem under investigation. The main advantage of this approach is that it generates dependence measures even if the multivariate Gaussian distribution does not apply, as the case is for the tails of the high frequency stock index returns distributions. The empirical evidence suggests that conventional Constant Conditional Correlation *GARCH* models produce very similar results not just quantitatively but qualitatively so according to the clustering analysis that was applied.

References

Ang, A., and G. Bekaert, 2002, International asset allocation with regime shifts, The Review of Financial Studies, 15, pp. 1137-1187.

Bekaert, G., C.R. Harvey and A. Ng, 2003, Market Integration and Contagion, Journal of Business,

Bollerslev, T., 1990, Modeling the coherence in Short-run Nominal Exchange Rates: A Multivariate Generalized ARCH Model, Review of Economics and Statistics, 72, pp. 498-505.

Boyer, B., M. Gibson and M. Loretan, 1999, Pitfalls in tests for changes in correlations, International Finance Discussion Papers, no. 597, Board of Governors of the Federal Reserve System.

Engle, R., 2002, Dynamic Conditional Correlation – A simple Class of Multivariate GARCH models, Journal of Business and Economic Statistics.

Glosten, L., R. Jaganathan and D. Runkle, 1993, On the Relation between the Expected Value and the Volatility of the Nominal Excess Return on Stocks, The Journal of Finance 48, 1779-1801.

Longin, F., and B. Solnik, 1995, Is the Correlation in international equity returns constant: 1960-1990?, Journal of International Money and Finance, 14, pp. 3-26.

Longin, F., and B. Solnik, 2001, Extreme Correlation of International Equity Markets, The Journal of Finance, vol. LVI, no.2, pp. 649-676.

MacQueen, J.B., 1967. Some methods for classification and analysis of multivariate observations. In: Proceedings of 5th Berkeley Symposium on Mathematical Statistics and Probability, 1. University of California Press, Berkeley, CA, pp. 281–297.

Neftçi, S. (2000), Value at Risk Calculations, Extreme Events, and Tail Estimation, Journal of Derivatives, spring, 23-38.

Poon, S-H., M. Rockinger, J. Tawn, 2004, Extreme Value Dependence in Financial Markets: Diagnostoics, Models, and Financial Implications, The Review of Financial Studies, no, 2, pp. 581-610.

Tiago de Oliveira, J., 1973, Statistical Extremes – A Survey, Center of Applied Mathematics, Lisbon.

Table 1: EVT Parameters

Parameter	ξ (Tail Index)				σ (scale parameter)				u (threshold)			
	Long	*Short*	*Long*	*Short*	*Long*	*Short*	*Long*	*Short*	*Long*	*Short*	*Long*	*Short*
In-sample Period	*5/1/87 - 5/3/01*		*2/11/90 - 31/12/04*		*5/1/87 - 5/3/01*		*2/11/90 - 31/12/04*		*5/1/87 - 5/3/01*		*2/11/90 - 31/12/04*	
Japan	0.069 (0.046)	0.150 (0.065)	-0.037 (0.047)	0.071 (0.058)	0.009	0.009	0.009	0.009	0.016	0.016	0.017	0.017
USA	0.245 (0.063)	0.126 (0.064)	0.055 (0.052)	0.082 (0.059)	0.006 (	0.006	0.007	0.006	0.012	0.012	0.012	0.012
Hong Kong	0.325 (0.078)	0.243 (0.083)	0.128 (0.062)	0.180 (0.061)	0.011	0.010	0.011	0.009	0.022	0.022	0.019	0.019
Taiwan	-0.172 (0.047)	0.046 (0.060)	0.009 (0.063)	0.030 (0.053)	0.019	0.013	0.013	0.013	0.025	0.025	0.021	0.021
Malaysia	0.265 (0.075)	0.411 (0.092)	0.206 (0.073)	0.338 (0.084)	0.012	0.009	0.011	0.010	0.020	0.020	0.018	0.018
Indonesia	0.275 (0.095)	0.427 (0.109)	0.183 (0.074)	0.174 (0.074)	0.012	0.013	0.011	0.011	0.021	0.021	0.018	0.018
Singapore	0.355 (0.084)	0.266 (0.079)	0.189 (0.068)	0.231 (0.067)	0.008	0.008	0.008	0.007	0.017	0.017	0.015	0.015
Thailand	0.116 (0.071)	0.190 (0.072)	0.151 (0.069)	0.283 (0.078)	0.016	0.017	0.013	0.014	0.026	0.026	0.025	0.025

Notation: Long (short) refers to negative (positive) returns. Standard errors in parentheses.

***Total In-sample Period observations**: 3696 (~15 years)*

Data Source:

Japan: Nikkei 255 Stock Average
USA: S&P 500 Composite
Hong Kong: Hang Seng Price Index
Taiwan: Stock Exchange Weighted Price Index
Malaysia: KLCI Composite Price Index
Indonesia: Jakarta Stock Exchange Composite Price Index
Singapore: Straits Times (New) Price Index
Thailand: SET 100 Basic Industries Index

Table 2: Correlation Estimates

Bivariate Model	MEVT (POT)				MVGARCH				UNCONDITIONAL	
	Long	Short	Long	Short	DCC(GJR)	CCC(GJR)	DCC(GJR)	CCC(GJR)		
In-sample Period	5/1/87 - 5/3/01		2/11/90 - 31/12/04		5/1/87 - 5/3/01		2/11/90 - 31/12/04		5/1/87 - 5/3/01	2/11/90 - 31/12/04
Japan – USA	0.320	0.279	0.320	0.312	0.252	0.279	0.176	0.292	0.318	0.293
Japan – Hong Kong	0.338	0.286	0.356	0.313	0.880	0.288	0.133	0.349	0.295	0.348
Japan – Taiwan	0.236	0.195	0.236	0.248	0.186	0.115	0.180	0.191	0.136	0.186
Japan – Malaysia	0.328	0.247	0.257	0.222	0.210	0.241	0.147	0.230	0.255	0.195
Japan – Indonesia	0.176	0.176	0.219	0.217	0.096	0.093	0.170	0.167	0.086	0.175
Japan – Singapore	0.361	0.313	0.375	0.309	0.376	0.283	0.365	0.318	0.357	0.329
Japan – Thailand	0.237	0.199	0.218	0.222	0.205	0.134	0.144	0.125	0.149	0.152
USA – Hong Kong	0.313	0.373	0.321	0.390	0.162	0.350	0.212	0.374	0.293	0.367
USA – Taiwan	0.222	0.222	0.232	0.252	0.314	0.131	0.298	0.180	0.142	0.199
USA – Malaysia	0.300	0.271	0.239	0.213	0.283	0.287	0.157	0.229	0.326	0.220
USA – Indonesia	0.221	0.159	0.265	0.216	0.119	0.123	0.161	0.164	0.113	0.180
USA – Singapore	0.418	0.338	0.393	0.306	0.291	0.372	0.207	0.326	0.480	0.335
USA – Thailand	0.261	0.237	0.237	0.235	0.265	0.197	0.176	0.167	0.210	0.188
Hong Kong – Taiwan	0.198	0.195	0.256	0.266	0.326	0.134	0.210	0.233	0.126	0.220
Hong Kong – Malaysia	0.452	0.337	0.423	0.324	0.308	0.378	0.356	0.336	0.370	0.357
Hong Kong – Indonesia	0.288	0.231	0.350	0.262	0.158	0.174	0.236	0.248	0.191	0.304
Hong Kong – Singapore	0.583	0.499	0.598	0.504	0.640	0.496	0.395	0.525	0.507	0.601
Hong Kong – Thailand	0.324	0.321	0.329	0.326	0.279	0.258	0.269	0.247	0.279	0.296
Taiwan – Malaysia	0.199	0.181	0.198	0.163	0.175	0.105	0.152	0.143	0.127	0.142
Taiwan – Indonesia	0.135	0.128	0.210	0.199	0.043	0.070	0.133	0.131	0.035	0.136
Taiwan – Singapore	0.243	0.213	0.286	0.267	0.543	0.140	0.209	0.228	0.163	0.233
Taiwan – Thailand	0.199	0.192	0.232	0.208	0.156	0.115	0.137	0.110	0.138	0.144
Indonesia – Malaysia	0.350	0.243	0.365	0.266	0.125	0.175	0.162	0.248	0.174	0.254
Indonesia – Singapore	0.362	0.314	0.425	0.337	0.053	0.213	0.204	0.300	0.232	0.371
Indonesia – Thailand	0.276	0.248	0.344	0.278	0.161	0.165	0.202	0.204	0.198	0.292
Malaysia – Singapore	0.619	0.500	0.491	0.393	0.501	0.575	0.337	0.445	0.563	0.432
Malaysia – Thailand	0.319	0.293	0.327	0.298	0.250	0.257	0.240	0.231	0.275	0.268
Singapore - Thailand	0.404	0.324	0.396	0.347	0.317	0.315	0.294	0.279	0.351	0.365

Notation: *POT* = Peaks over Threshold methods for the generation of the extreme observations. *CCC*= constant conditional correlation method. *DCC*=Dynamic conditional correlation method. *GJR*= Glosten, L., R. Jaganathan and D. Runkle, (1993). Other notation as in table 1.

Table 3: Correlation K-Means Clustering

Bivariate Model	EVT (POT)				MVGARCH				UNCONDITIONAL	
	Long	Short	Long	Short	DCC(GJR)	CCC(GJR)	DCC(GJR)	CCC(GJR)		
In-sample Period	5/1/87 - 5/3/01		2/11/90 - 31/12/04		5/1/87 - 5/3/01		2/11/90 - 31/12/04		5/1/87 - 5/3/01	2/11/90 - 31/12/04
Japan – USA	2	2	2	2	1	2	1	2	2	2
Japan – Hong Kong	2	2	2	2	3	2	1	2	2	2
Japan – Taiwan	1	1	1	1	1	1	1	1	1	1
Japan – Malaysia	2	1	1	1	1	2	1	2	2	1
Japan – Indonesia	1	1	1	1	1	1	1	1	1	1
Japan – Singapore	2	2	2	2	2	2	3	2	2	2
Japan – Thailand	1	1	1	1	1	1	1	1	1	1
USA – Hong Kong	2	2	2	2	1	2	2	3	2	2
USA – Taiwan	1	1	1	1	1	1	3	1	1	1
USA – Malaysia	2	2	1	1	1	2	1	2	2	1
USA – Indonesia	1	1	1	1	1	1	1	1	1	1
USA – Singapore	2	2	2	2	1	2	2	2	3	2
USA – Thailand	1	1	1	1	1	1	1	1	1	1
Hong Kong – Taiwan	1	1	1	1	1	1	2	2	1	1
Hong Kong – Malaysia	2	2	2	2	1	2	3	2	2	2
Hong Kong – Indonesia	2	1	2	1	1	1	2	2	1	2
Hong Kong – Singapore	3	3	3	3	2	3	3	3	3	3
Hong Kong – Thailand	2	2	2	2	1	2	2	2	2	2
Taiwan – Malaysia	1	1	1	1	1	1	1	1	1	1
Taiwan – Indonesia	1	1	1	1	1	1	1	1	1	1
Taiwan – Singapore	1	1	1	1	2	1	2	2	1	1
Taiwan – Thailand	1	1	1	1	1	1	1	1	1	1
Indonesia – Malaysia	2	1	2	1	1	1	1	2	1	1
Indonesia – Singapore	2	2	2	2	1	1	2	2	2	2
Indonesia – Thailand	1	1	2	1	1	1	2	1	1	2
Malaysia – Singapore	3	3	3	2	2	3	3	3	3	2
Malaysia – Thailand	2	2	2	2	1	2	2	2	2	2
Singapore - Thailand	2	2	2	2	1	2	3	2	2	2

K-Means Centers

K-Groups	EVT (POT)				MVGARCH				UNCONDITIONAL	
	Long	Short	Long	Short	DCC(GJR)	CCC(GJR)	DCC(GJR)	CCC(GJR)		
In-sample Period	5/1/87 - 5/3/01		2/11/90 - 31/12/04		5/1/87 - 5/3/01		2/11/90 - 31/12/04		5/1/87 - 5/3/01	2/11/90 - 31/12/04
G_1 : Low Correlation	0.217	0.204	0.237	0.233	0.206	0.139	0.156	0.158	0.142	0.187
G_2 : Medium Correlation	0.348	0.313	0.363	0.332	0.515	0.301	0.221	0.273	0.305	0.335
G_3 : High Correlation	0.601	0.499	0.544	0.504	0.880	0.535	0.341	0.448	0.517	0.601

Notation: 1,2,3 refer to the classification to low, medium and high correlation.